bit.ly/mvnv-tutorial

A TUTORIAL ON

VISUALIZING MULTIVARIATE NETWORKS

CAROLINA NOBRE, MARC STREIT, ALEXANDER LEX

visualization design lab

THE UNIVERSITY OF UTAH

JOHANNES KEPLER UNIVERSITY LINZ

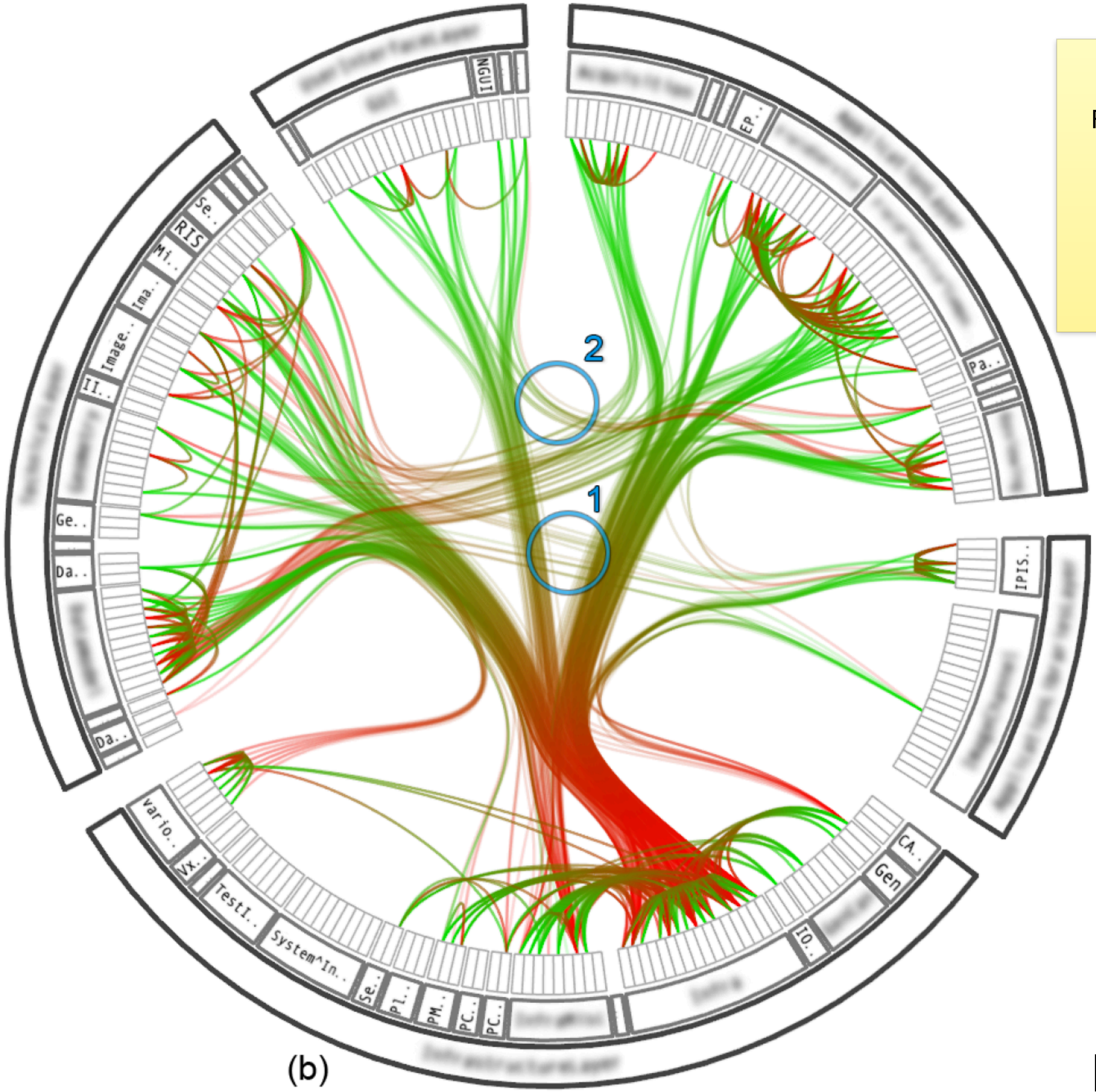

teacher
friends
competitors
friends
siblings
ex-boyfriend
coworkers
parent-child
siblings
married
friends
Photo by Rob Curran


Name: Samuel
Age: 41
Job: Nurse
Name: Julia
Age: 34
Job: Vet
Name: Ellen
Age: 31
Job: Actress
Name: Gordon
Age: 54
Job: Chef
Name: Roger
Age: 51
Job: Doctor
Name: Camille
Age: 42
Job: Teacher
Photo by Rob Curran

A MULTIVARIATE NETWORK IS
NETWORK TOPOLOGY +
NODE AND EDGE ATTRIBUTES


LinkedIn
LIVEJOURNAL
foursquare
vimeo
Insta
YouTube
facebook
Blogger
my
flickr
Behance
instagram
twitter
Like
tumblr.

Glyoxylate cycle
OXALYL-CoA
OXALATE
OXALYL-CoA DECARBOXYLASE
OXALATE DECARBOXYLASE
OXALATE-CoA-TRANSFERASE
FERREDIOXIN (red)
FERREDIOXIN (ox.)
2-OXO-GLUTARATE SYNTHASE
Deficient in hyperoxaluria I
PYRUVATE
ALANINE-GLYOXYLATE TRANSAMINASE
L-ALANINE
PyrP
CO_2
H_2O
CoA-SH
NADPH + H+
NADP+
GLYOXYLATE DEHYDROGENASE (ACYLATING)
$FMNH_2$ · E
(S)-2-HYDROXY ACID DEHYDROGENASE
FMN · E
O_2
H_2O_2
GLYOXYLATE
D-AMINO ACID OXIDASE
NH_3
FAD
NAD+
NADH + H+
GLYOXYLATE REDUCTASE
(S)-2-HYDROXY-ACID OXIDASE
GLYCINE TRANSAMINASE
L-GLUT-
2-OXO-GLUTARATE
ThPP
Mg^{++}



(b)

Find figure without 1/2

Holten and Wijk, 2009

SURVEYED 205 PAPERS FROM 1991 – 2018

Technique Papers, Evaluation Papers, Application Papers

EUROVIS 2019
R. S. Laramee, S. Oeltze, and M. Sedlmair
(Guest Editors)

Volume 38 (2019), Number 3
STAR – State of The Art Report

The State of the Art in Visualizing Multivariate Networks

C. Nobre[1], M. Meyer[1], M. Streit[2], and A. Lex[1]

[1]University of Utah, Utah, USA
[2]Johannes Kepler University Linz, Austria

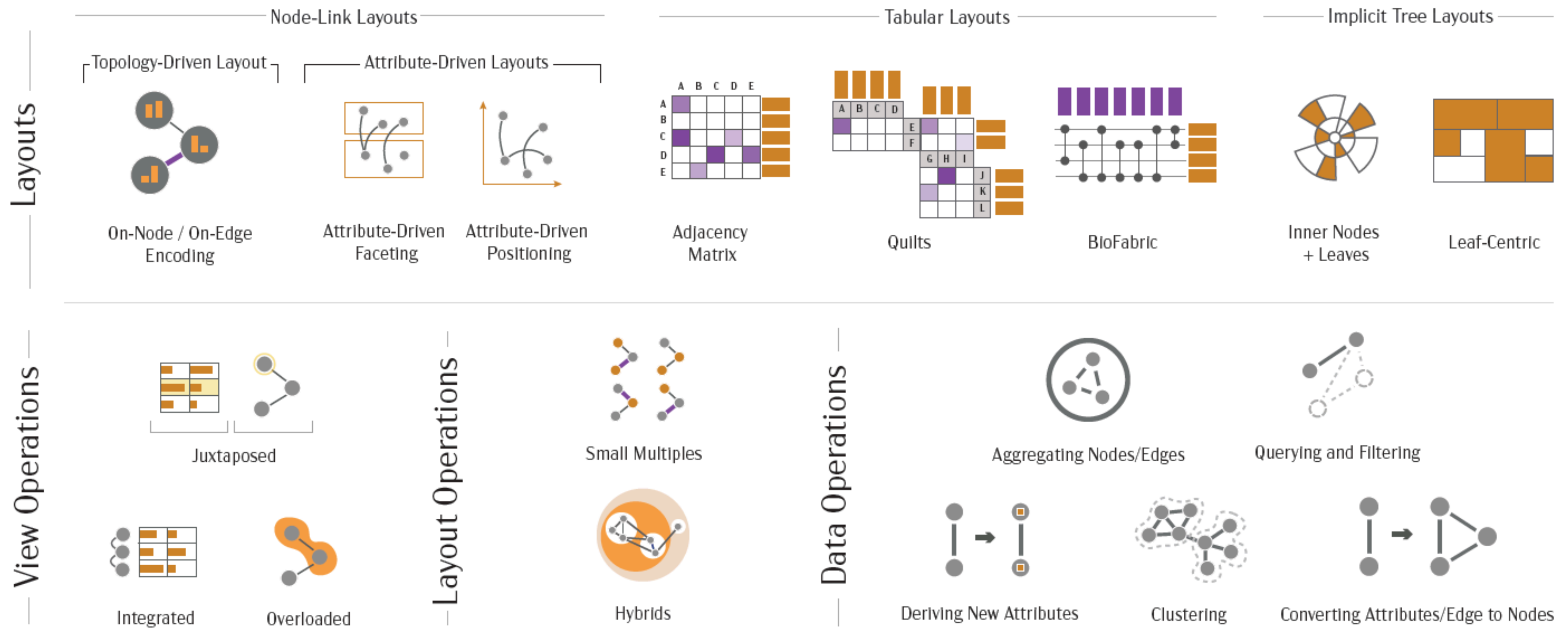
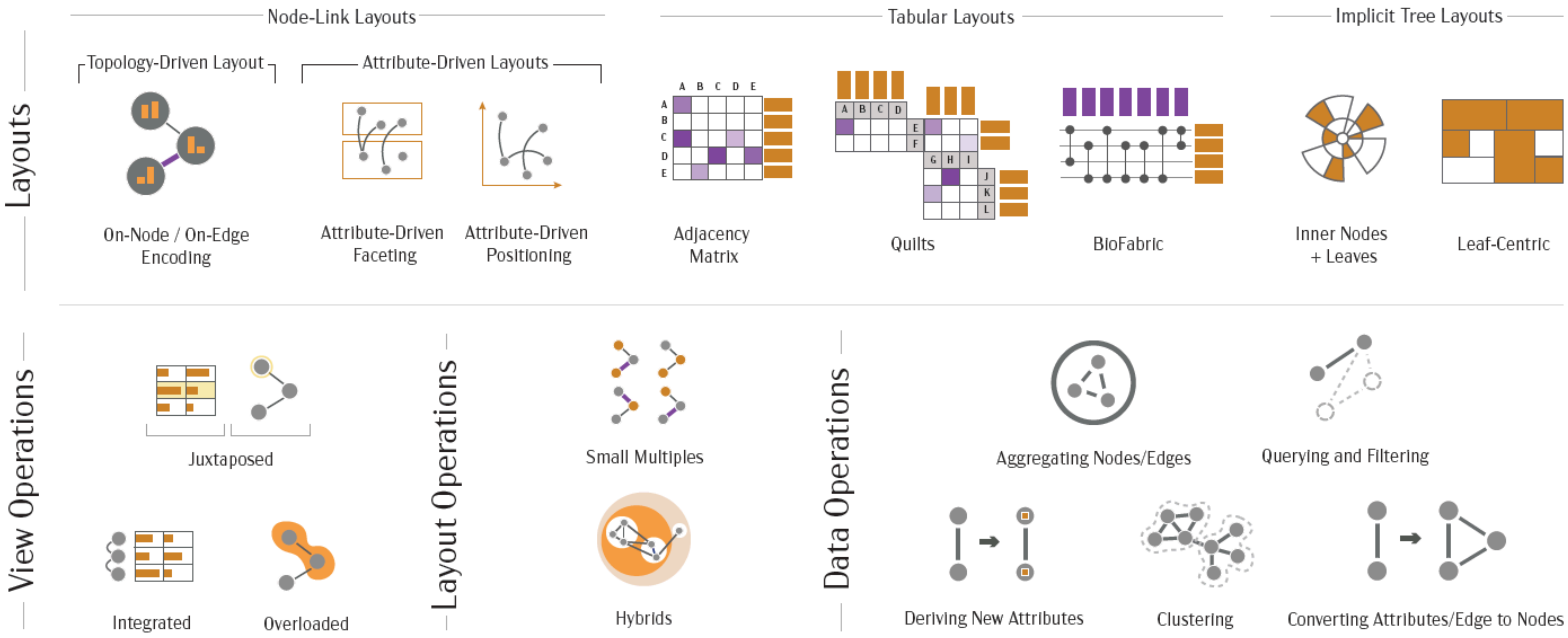


Figure 1: *A typology of operations and layouts used in multivariate network visualization.* ***Layouts*** *describe the fundamental choices for encoding multivariate networks.* ***View Operations*** *capture how topology and attribute focused visualizations can be combined.* ***Layout Operations*** *are applied to basic layouts to create specific visualization techniques.* ***Data Operations*** *are used to transform a network or derive attributes before visualizations. The colors reflect node attributes (orange), edge attributes (purple), and topology (grey).*

Abstract

Multivariate networks are made up of nodes and their relationships (links), but also data about those nodes and links as attributes. Most real-world networks are associated with several attributes, and many analysis tasks depend on analyzing both, relationships and attributes. Visualization of multivariate networks, however, is challenging, especially when both the topology of the network and the attributes need to be considered concurrently. In this state-of-the-art report, we analyze current practices and classify techniques along four axes: layouts, view operations, layout operations, and data operations. We also provide an analysis of tasks specific to multivariate networks and give recommendations for which technique to use in which scenario. Finally, we survey application areas and evaluation methodologies.


Layouts
Node-Link Layouts
Topology-Driven Layout
Attribute-Driven Layouts
On-Node / On-Edge Encoding
Attribute-Driven Faceting
Attribute-Driven Positioning
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BioFabric
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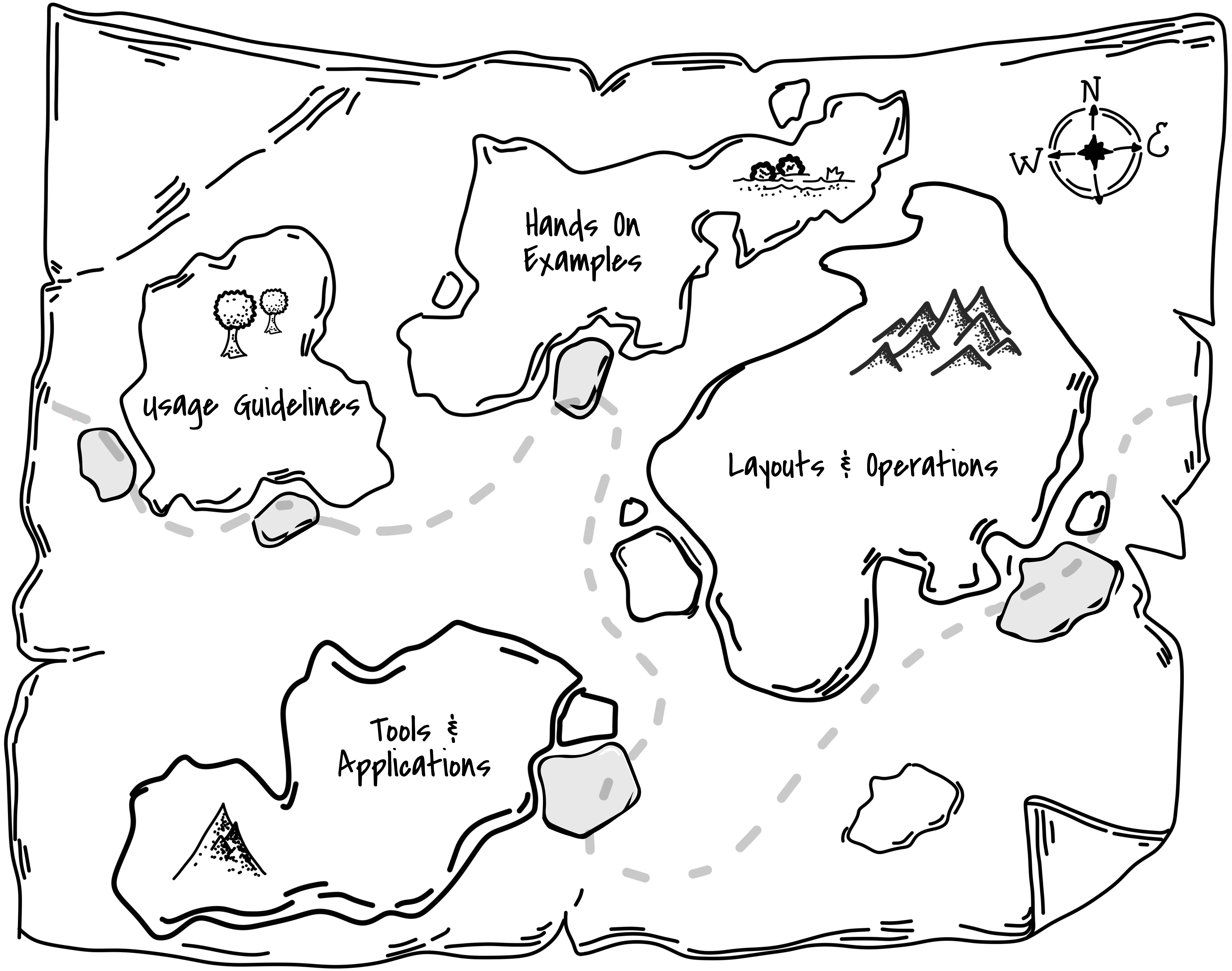
View Operations
Juxtaposed
Integrated
Overloaded
Layout Operations
Small Multiples
Hybrids
Data Operations
Aggregating Nodes/Edges
Querying and Filtering
Deriving New Attributes
Clustering
Converting Attributes/Edge to Nodes

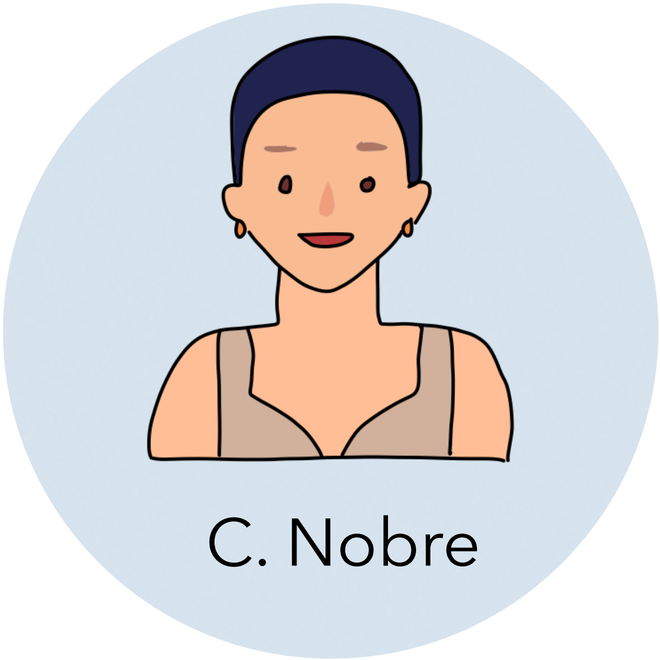
Land of Multivariate Networks

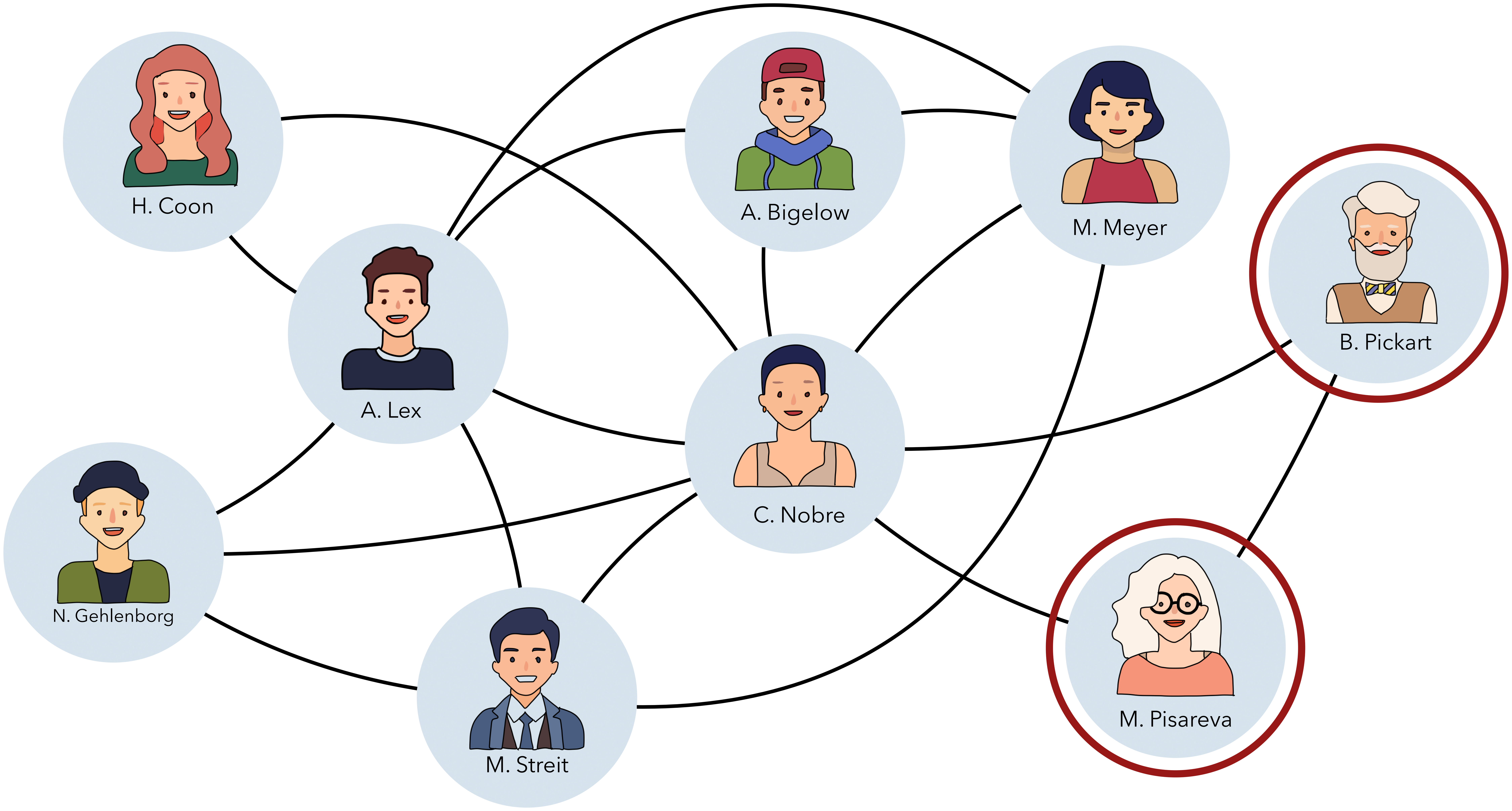


MVNV Tasks

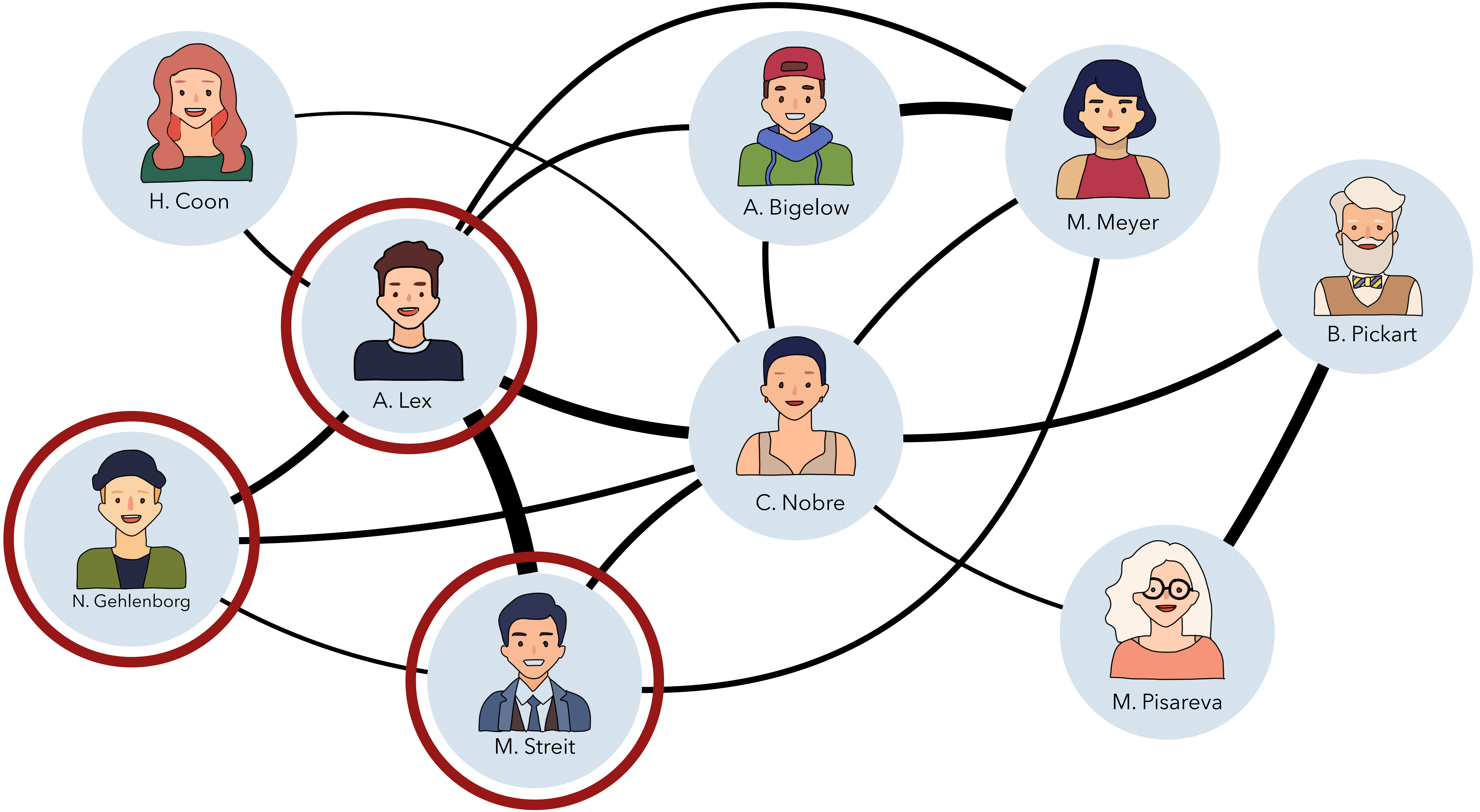
How is an MVN task different than a regular graph task?

MVN Tasks rely on both the topology of the network and the attributes of the nodes and edges

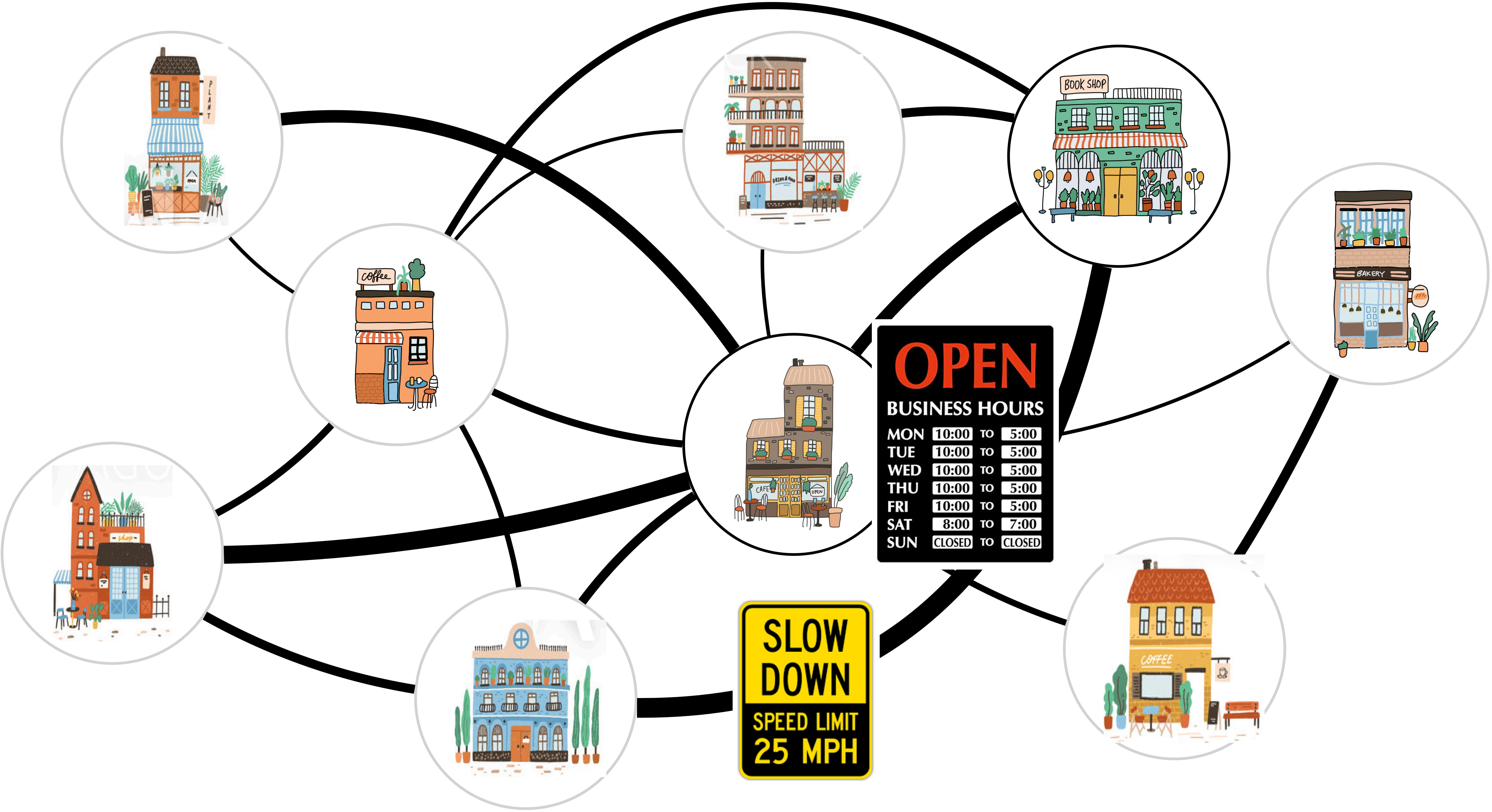

C. Nobre



How many of my collaborators are from the oceanography field?



Which cluster of authors has the highest number of combined collaborations?



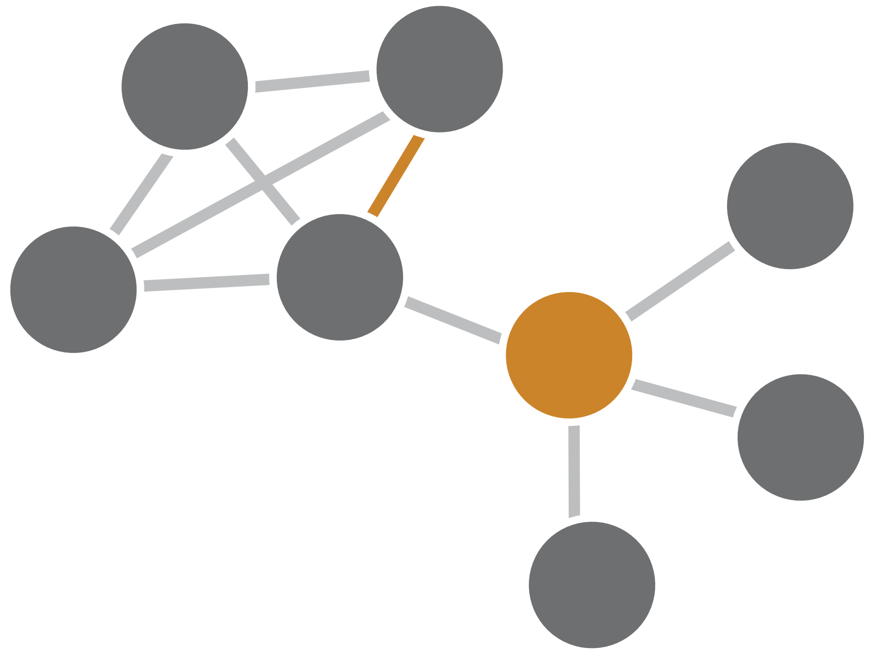
What is an efficient way I can complete all my errands?

- How many of my collaborators are in the oceanography field?
- Which cluster has the highest number of collaborations?
- What is the fastest route to get all my errands done?

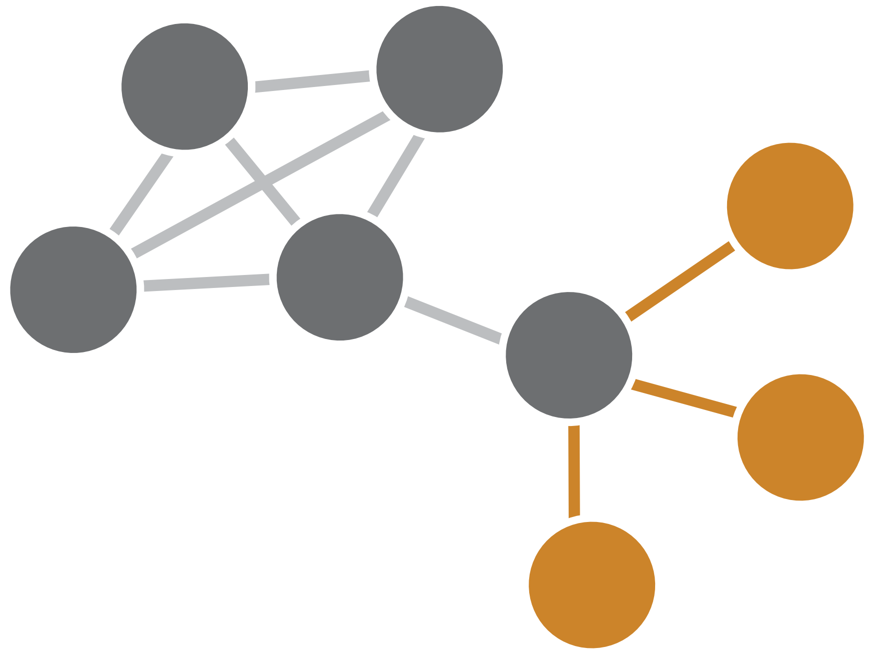
Tasks that rely on the **topology** of the network and the **attributes** of the nodes and edges

MVNV tasks are applied to topological structures

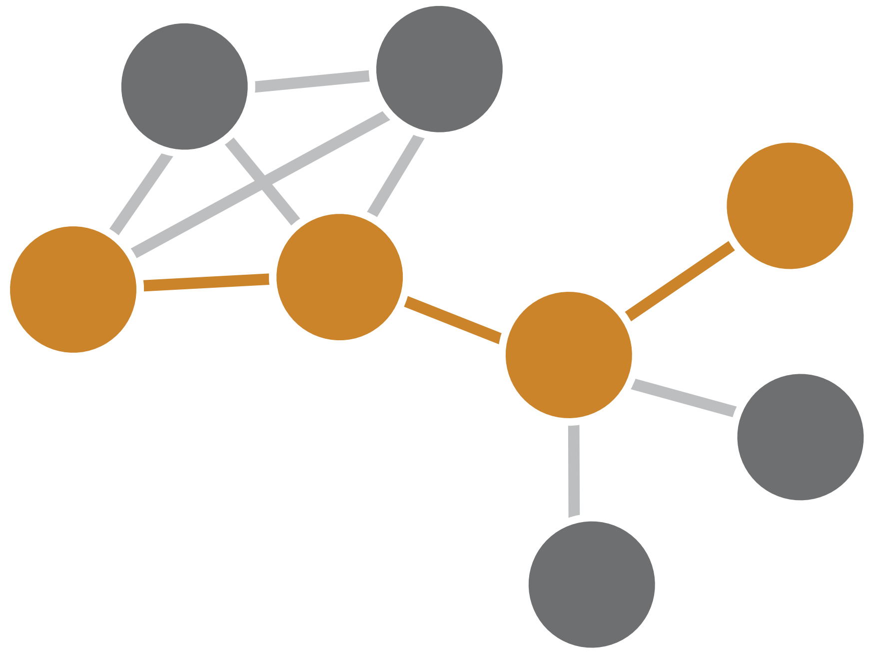
Single Node/Edge



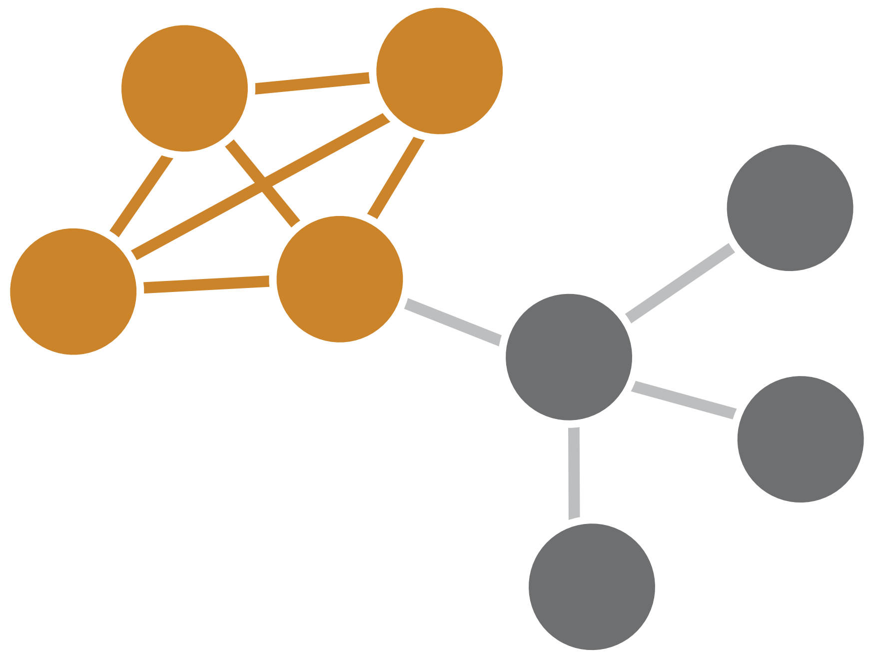
Node Neighbors



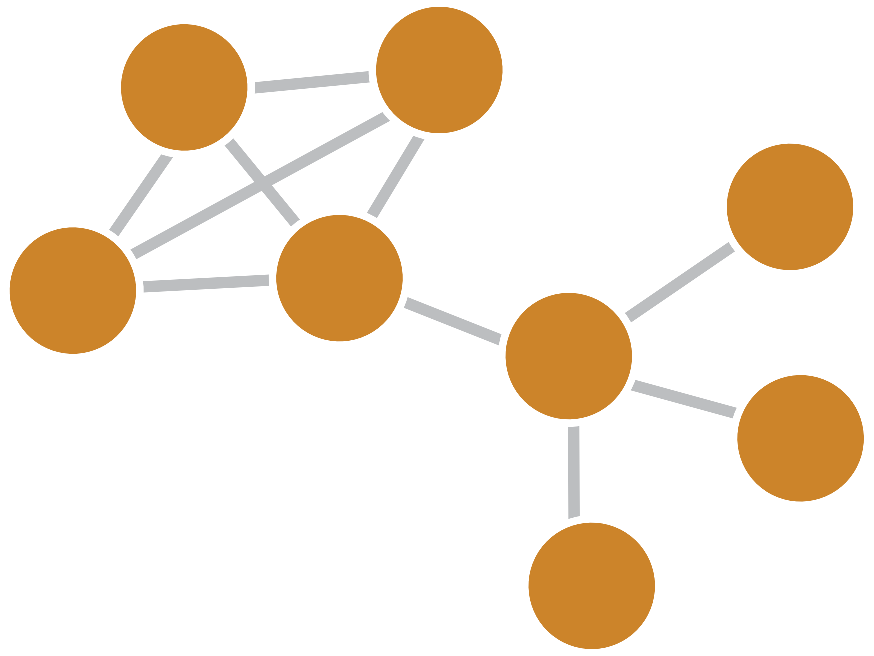
Path



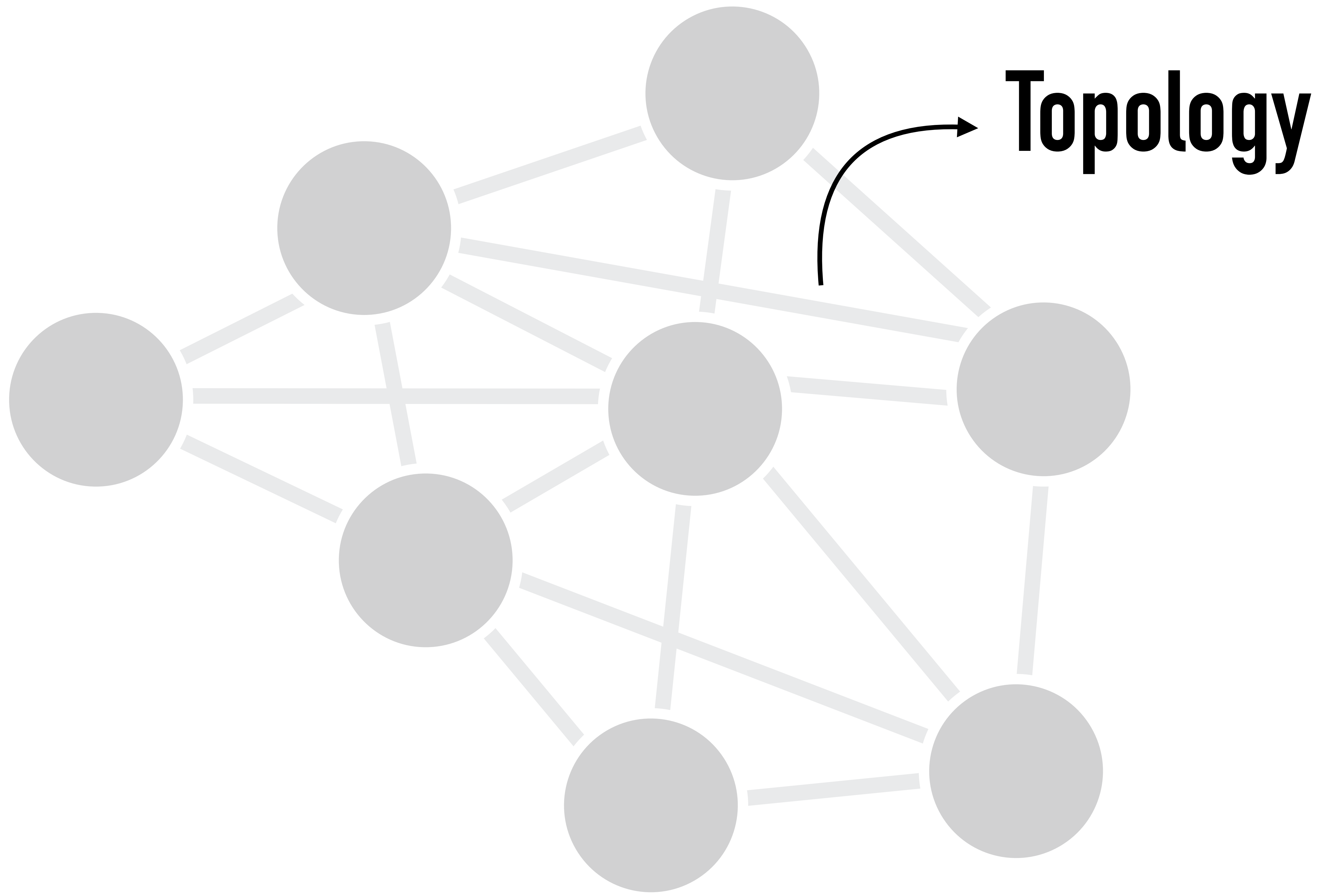
Cluster

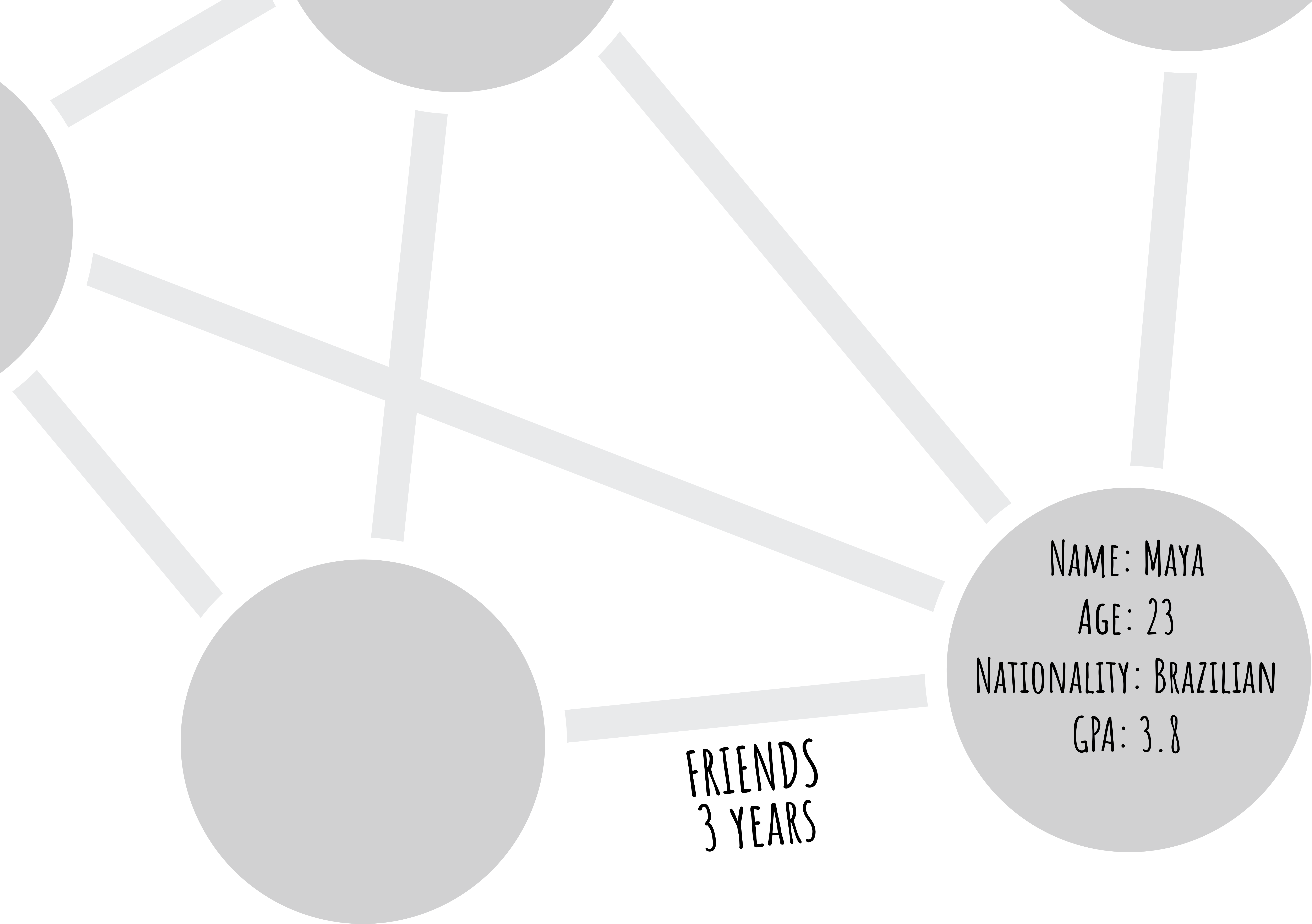


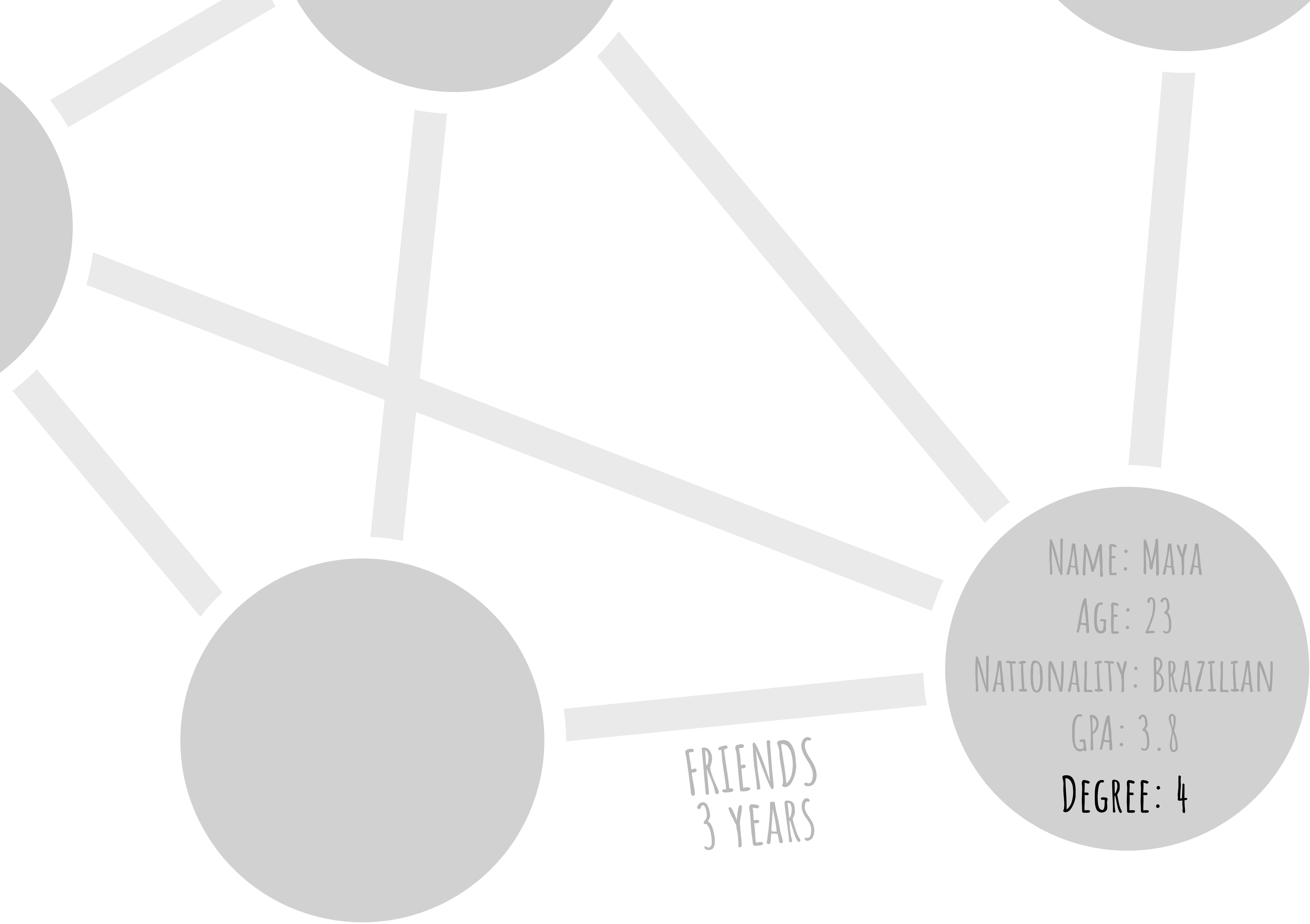
Network/Subnetwork

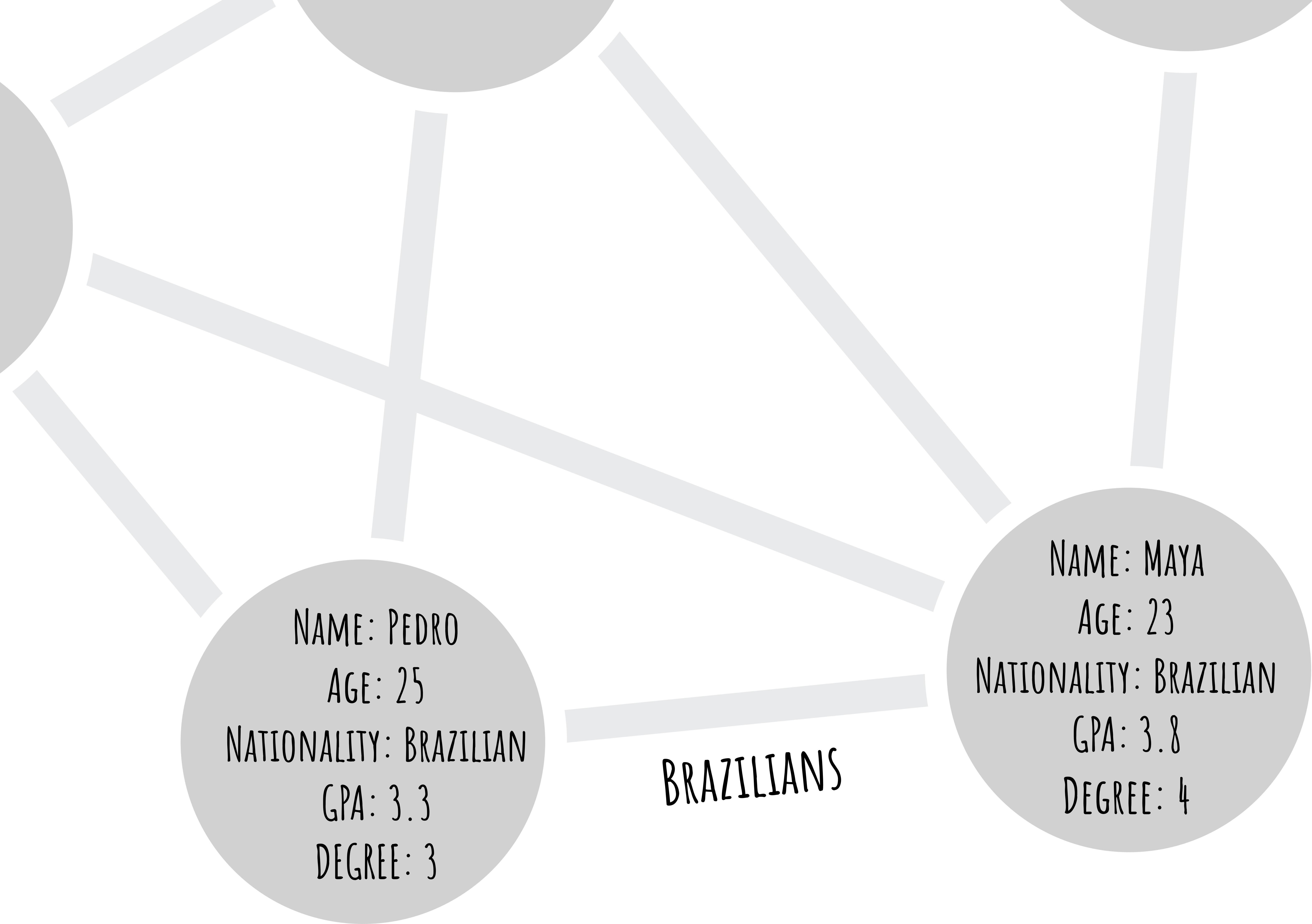


Network and Attribute Characteristics

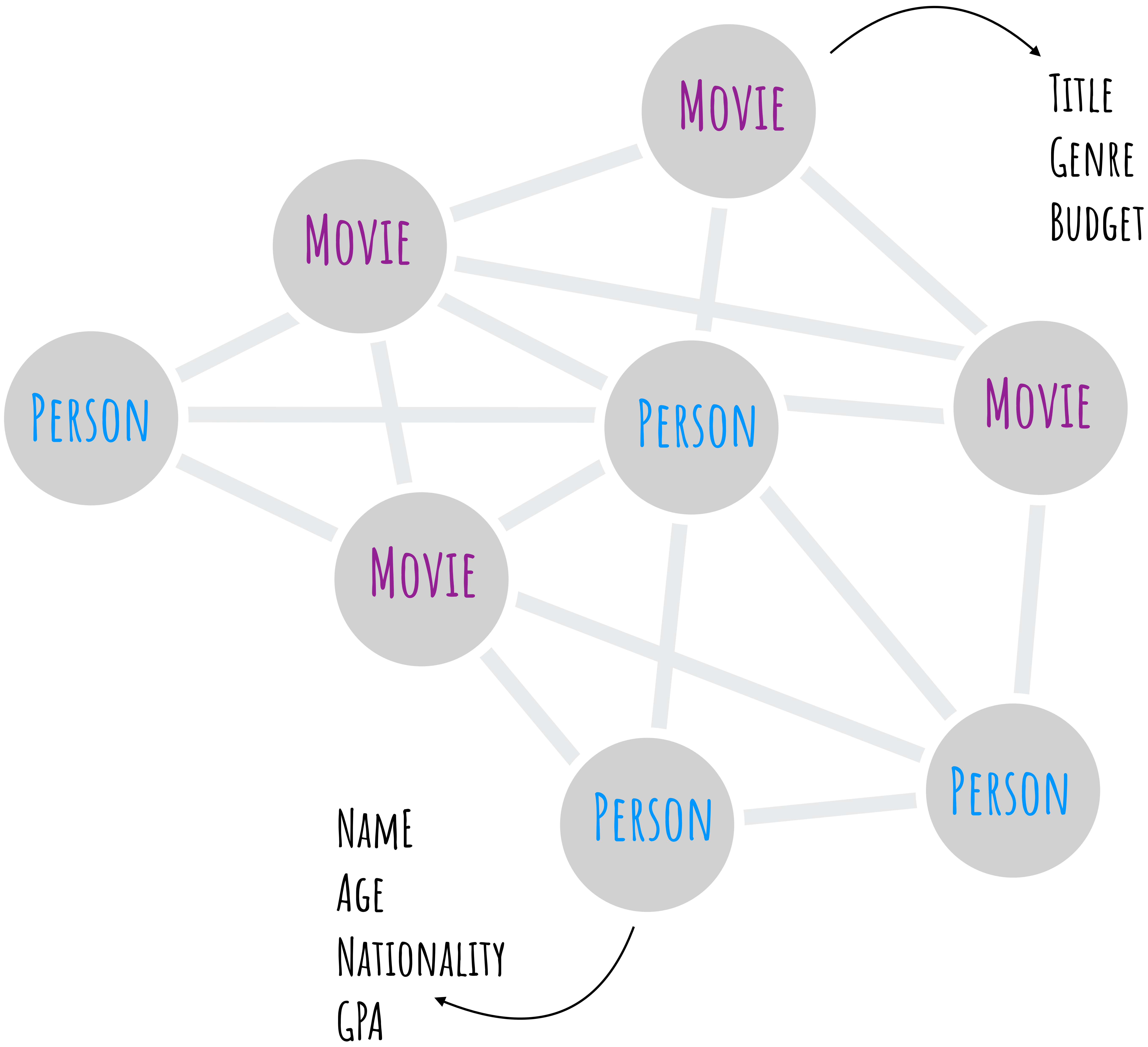

Topology


Name: Maya
Age: 23
Nationality: Brazilian
GPA: 3.8
FRIENDS
3 YEARS

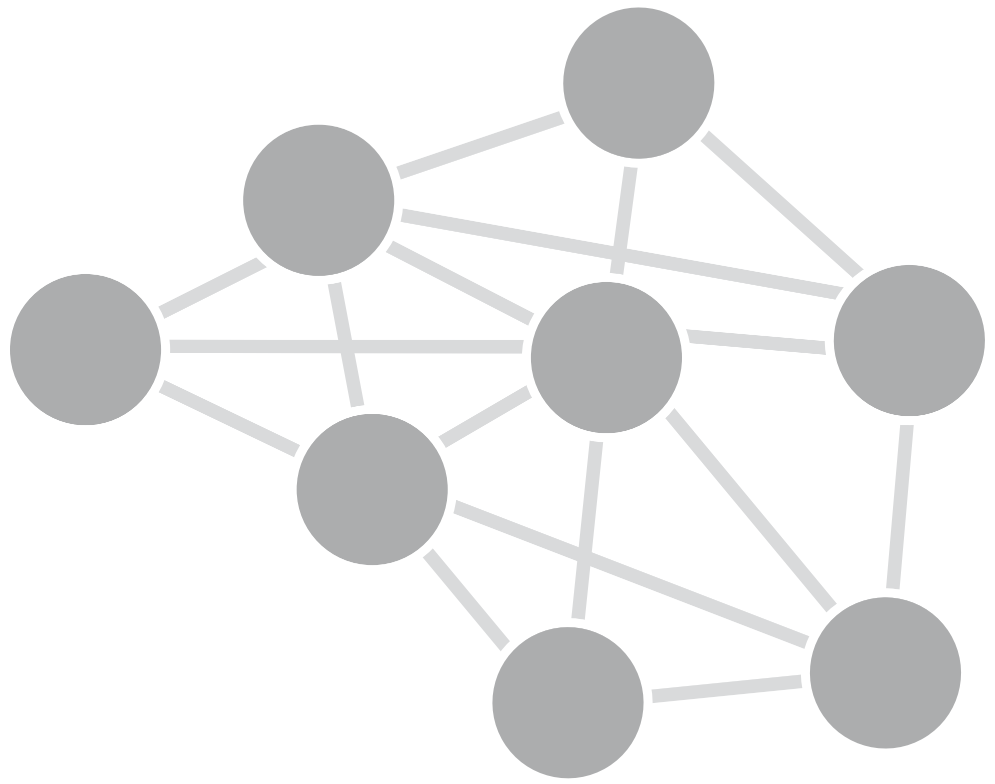

Name: Maya
Age: 23
Nationality: Brazilian
GPA: 3.8
Degree: 4
Friends
3 years



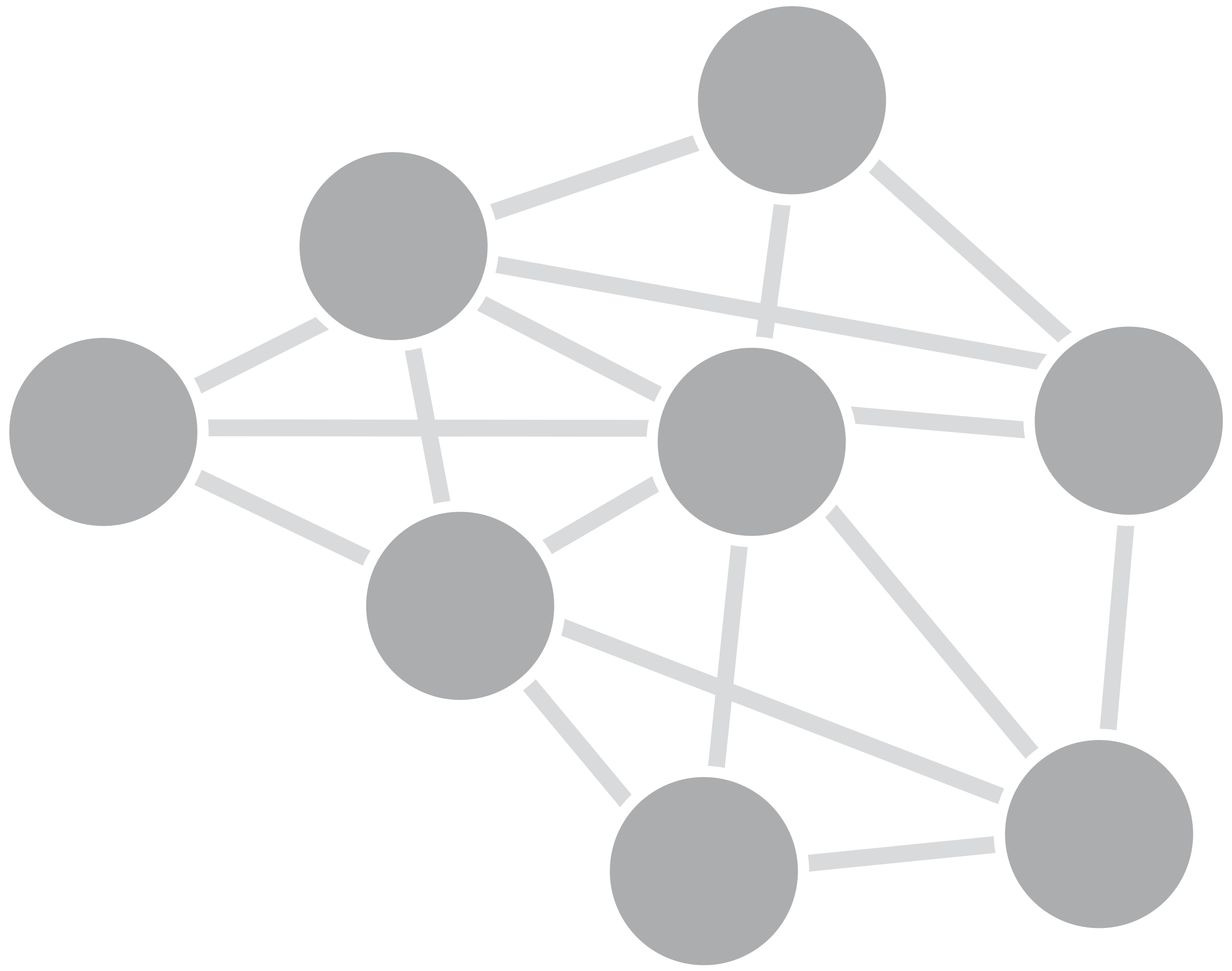
Name: Pedro
Age: 25
Nationality: Brazilian
GPA: 3.3
Degree: 3
Brazilians
Name: Maya
Age: 23
Nationality: Brazilian
GPA: 3.8
Degree: 4


Movie
Title
Genre
Budget
Movie
Person
Person
Movie
Movie
Person
Person
Name
Age
Nationality
GPA

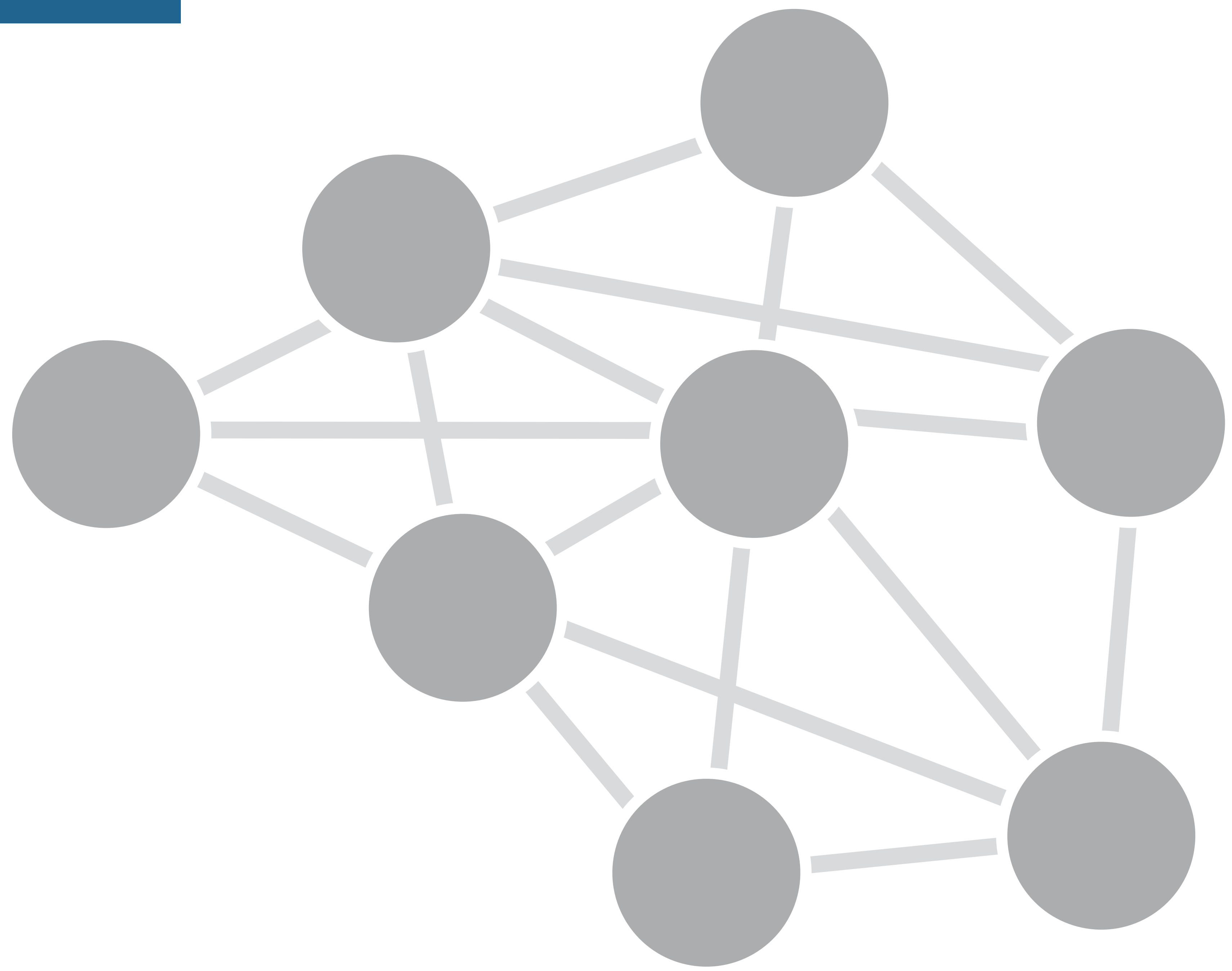
Network Size



Small
<100

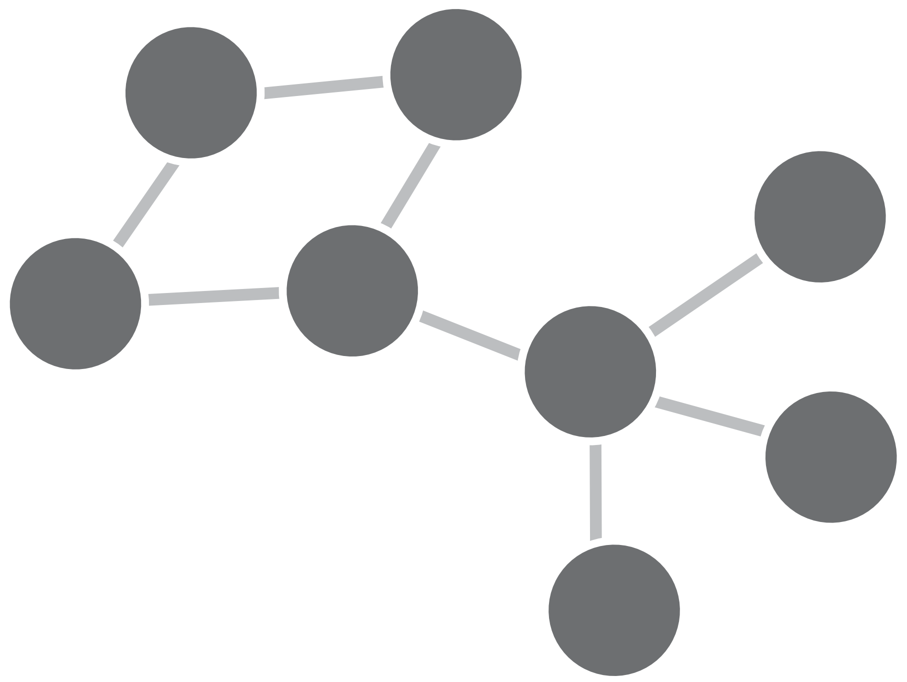


Medium
100–1000

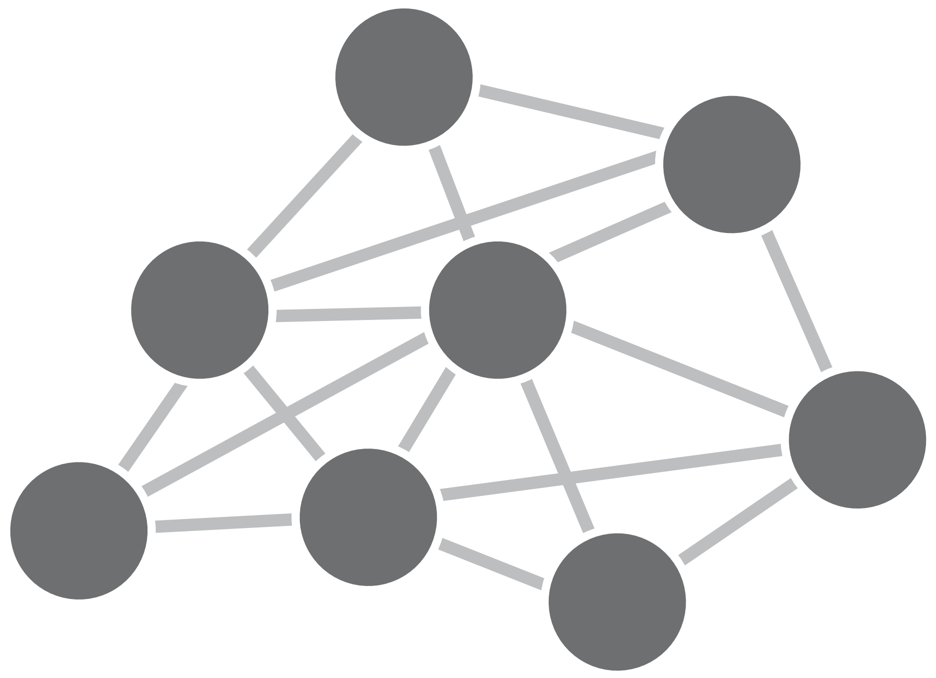


Large
>1000

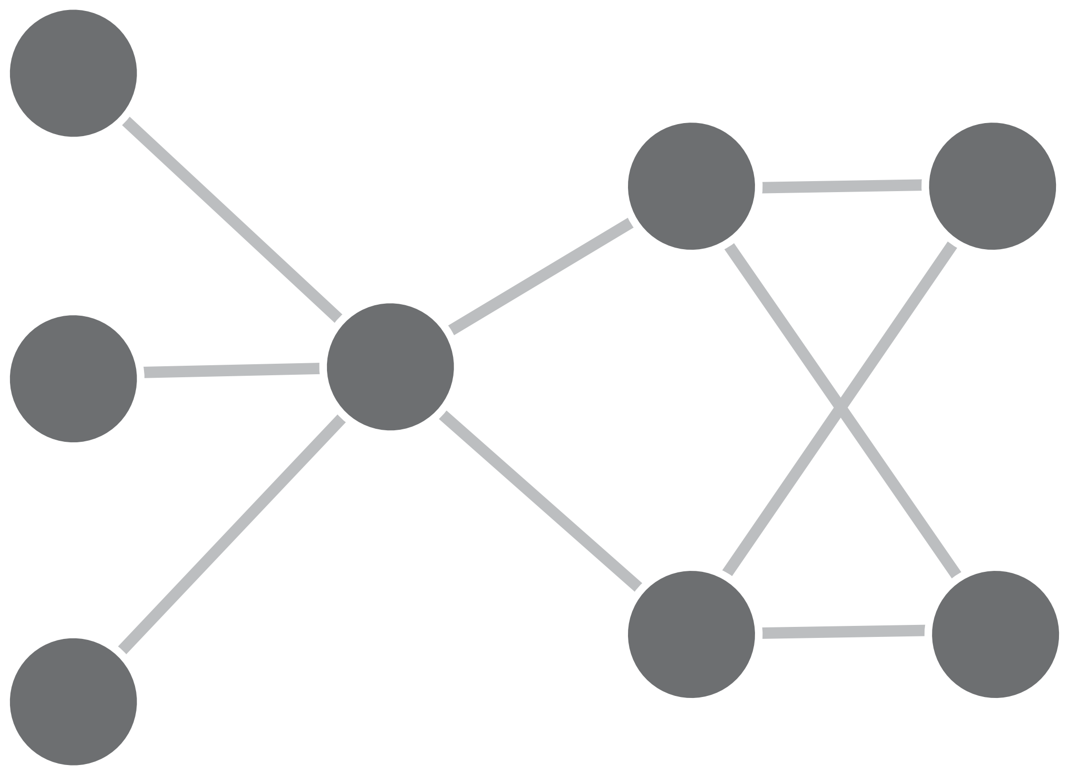
Network Types



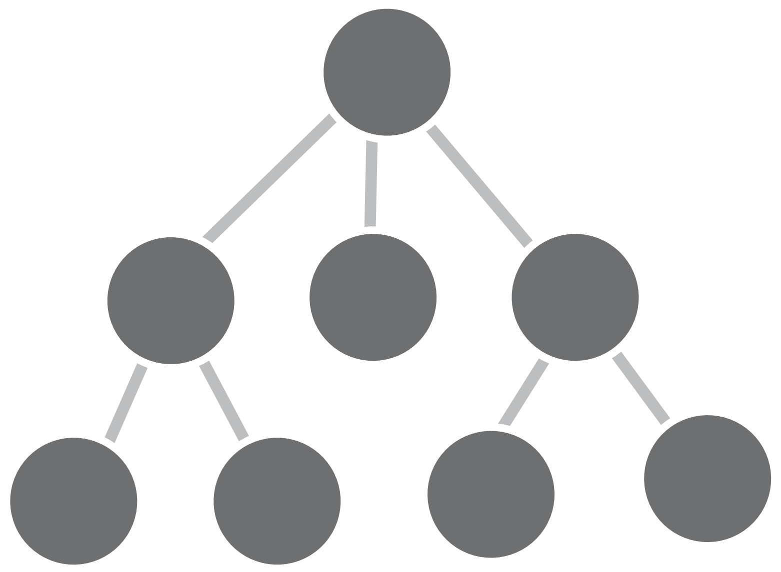
Sparse



Dense



Layered

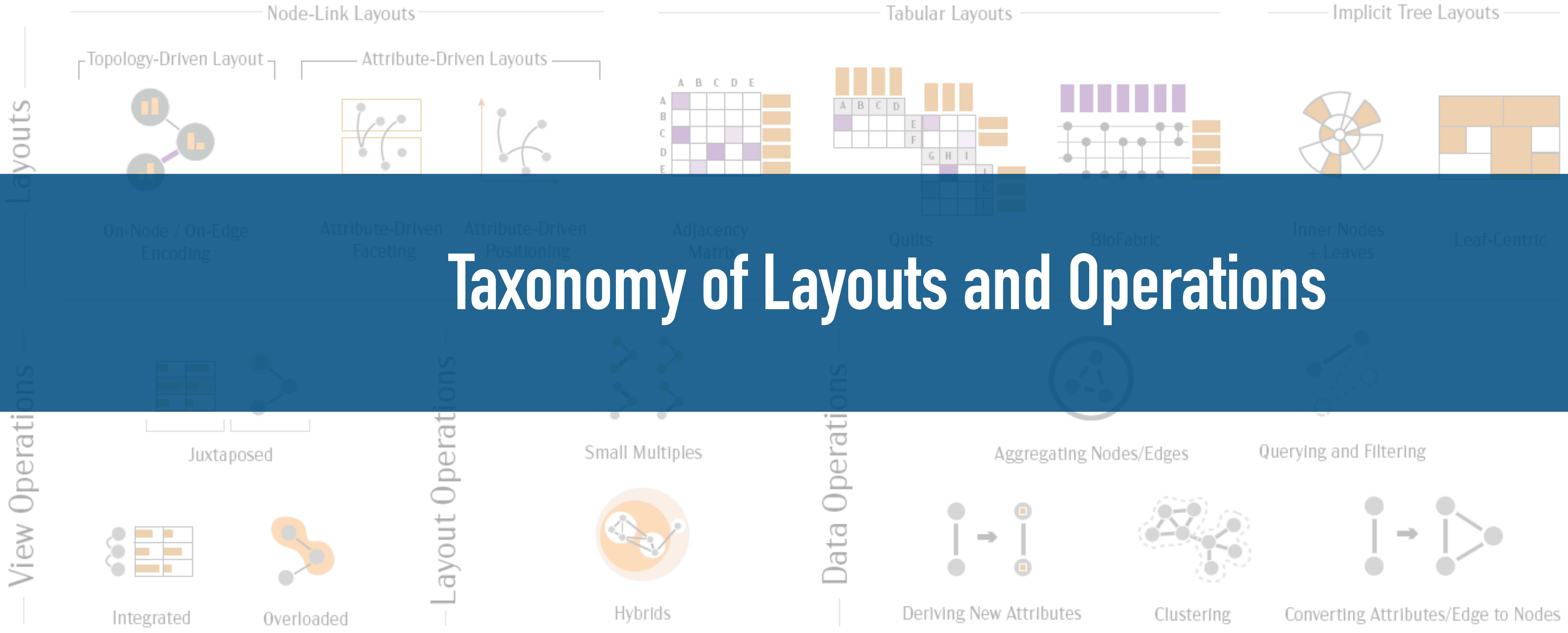


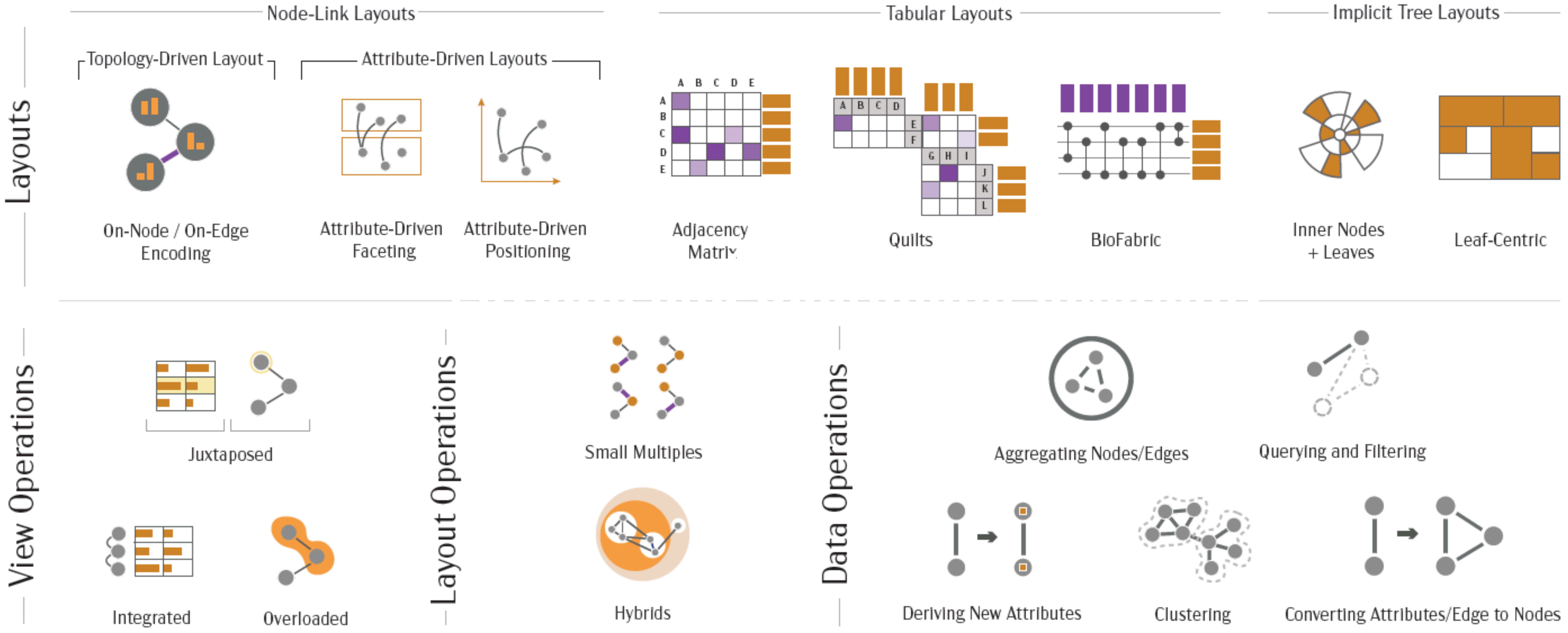
Trees

Slide on attribute data types

For node attributes, we distinguish between few (less than five) and many (more than five), but also give more detailed ranges when discussing a specific technique.We considered a category for a high number of attributes (e.g., hundreds), but realized that the same set of techniques that support five or more attributes well also support larger numbers of attributes. We also discuss data type properties when appropriate. We further distinguish between homogeneous networks with respect to node types, i.e., all nodes are of the same type (e.g., only actors), and heterogeneous networks, i.e., the network has more than one node type (e.g., actors and movies).
We categorize analogously for edge attributes, albeit we consider few to be less than three and many to be three or more attributes. Finally, we distinguish between homogeneous and heterogeneous edges.

Taxonomy of Layouts and Operations





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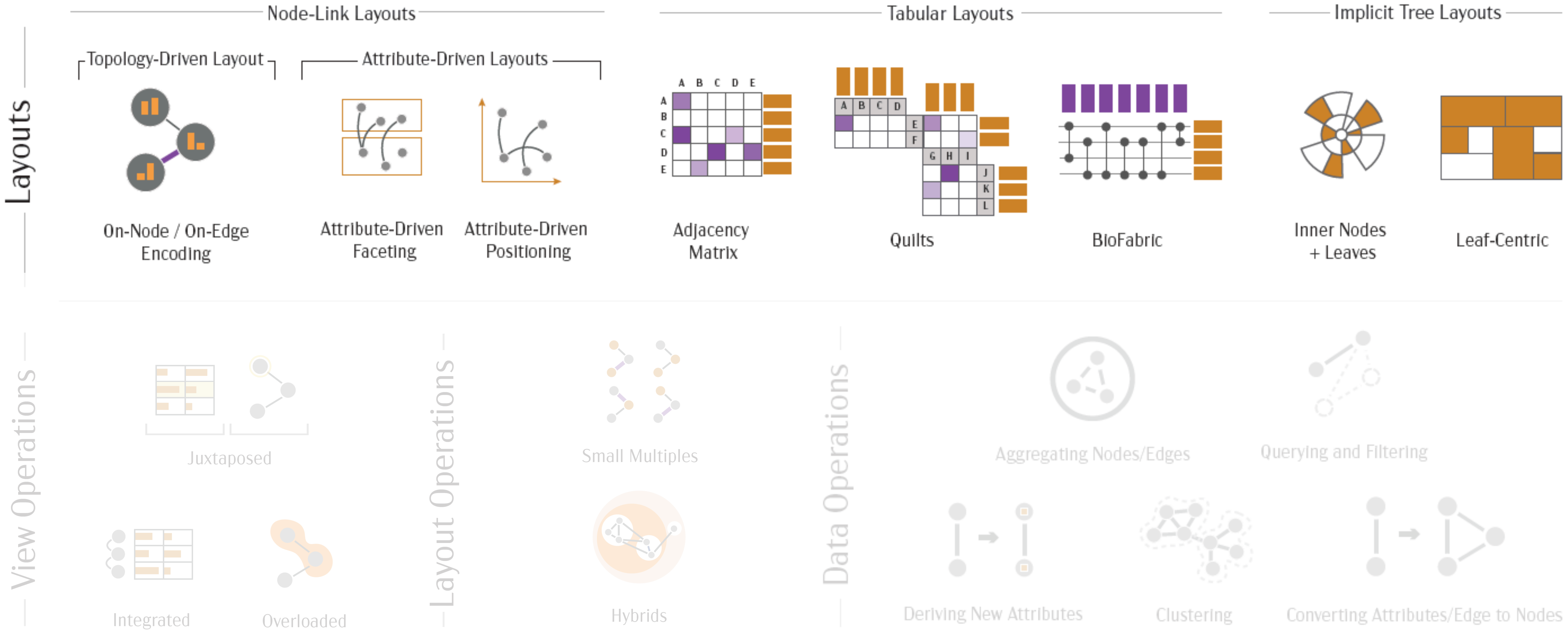
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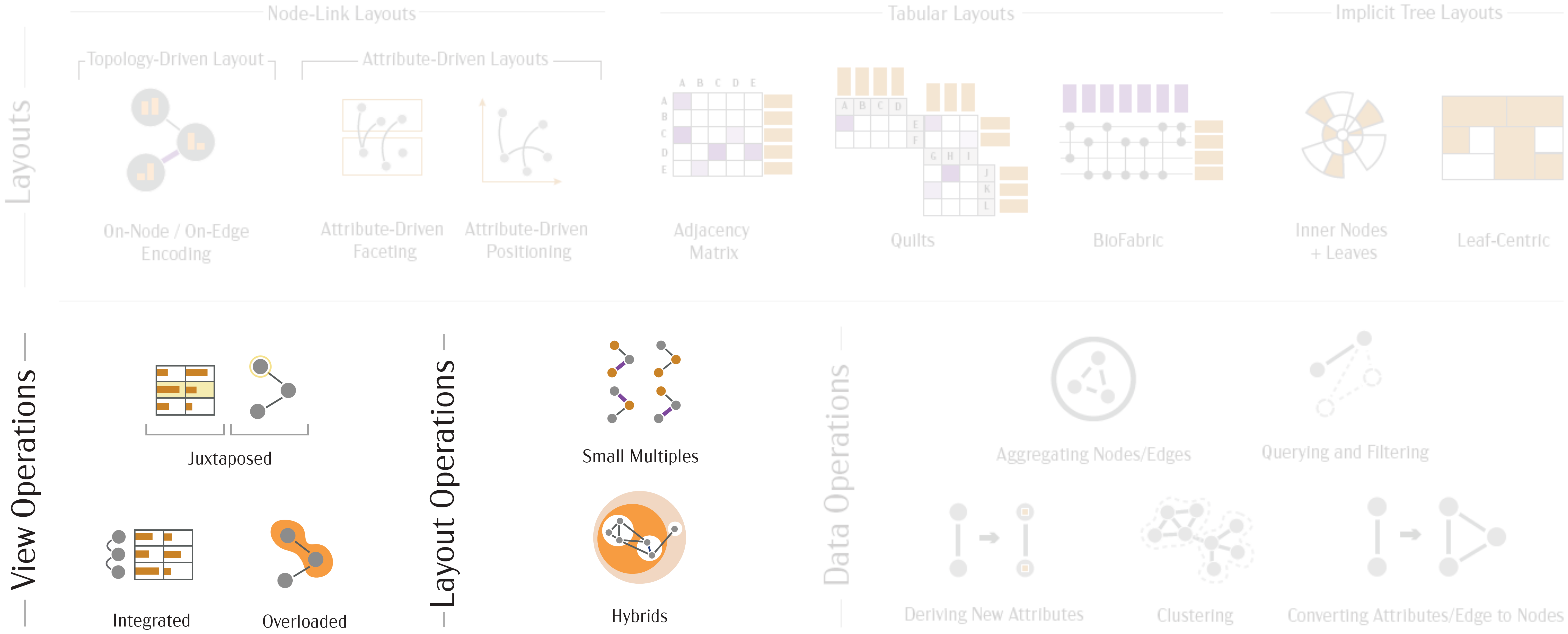

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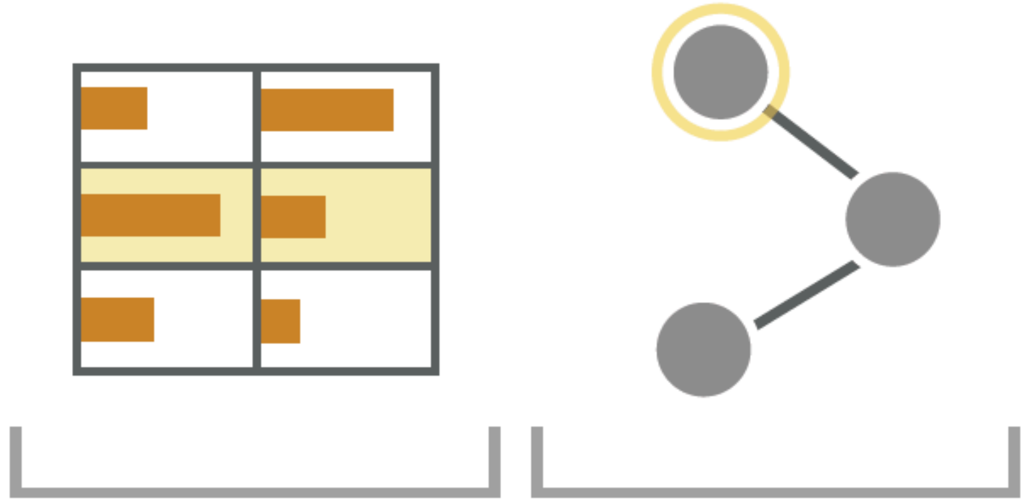
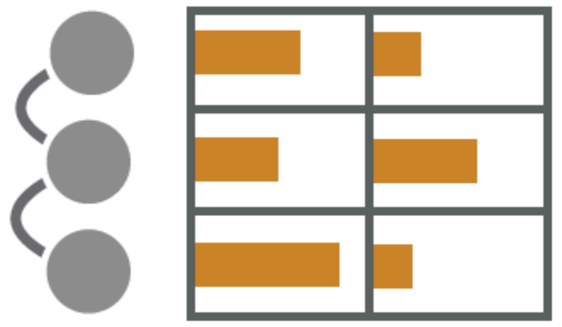
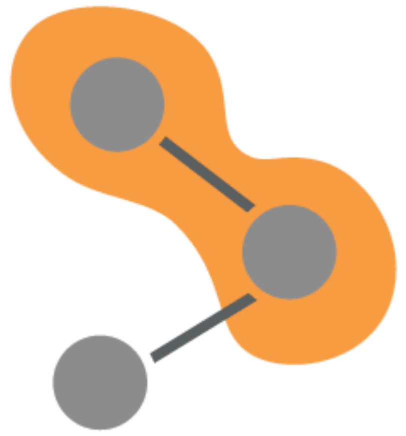
View Operations



Juxtaposed



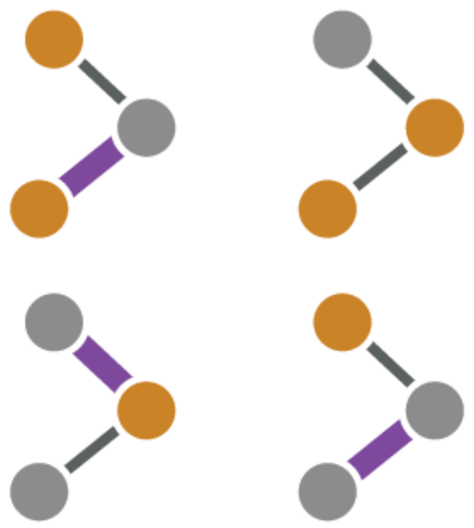
Integrated



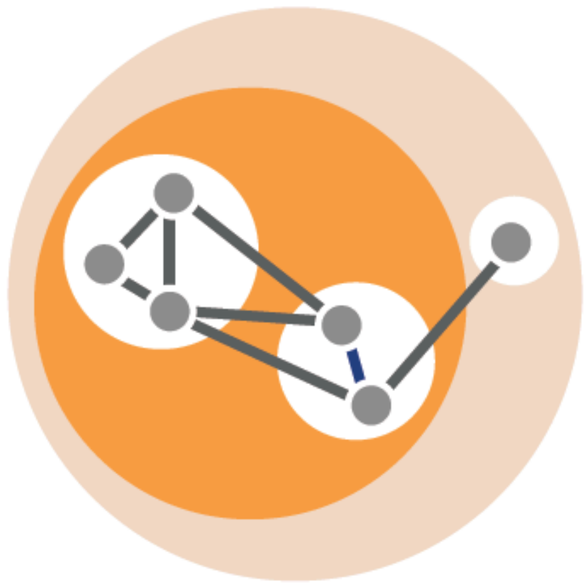
Overloaded

Separate views for Topology and Attributes

Layout Operations

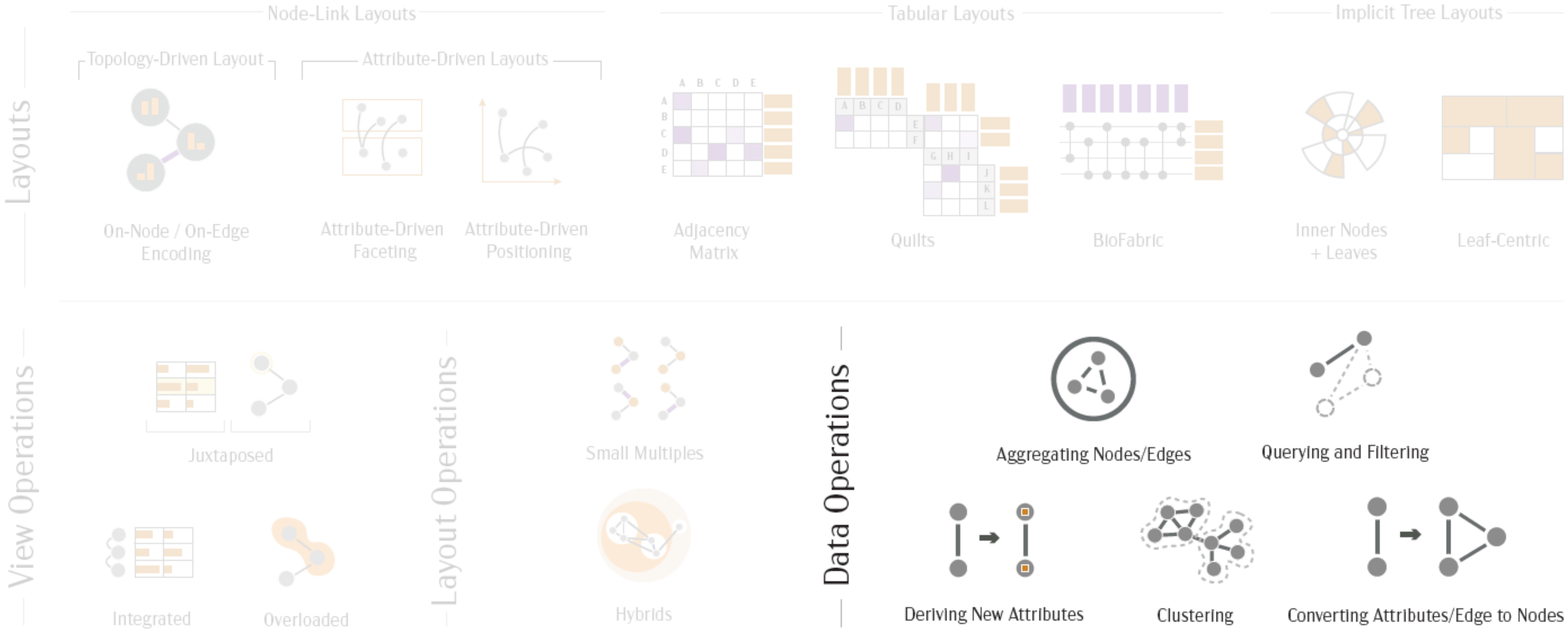


Small Multiples



Hybrids

Multiple layouts for Topology or Attributes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		Size			Type				Node Attributes				Edge Attributes				Topolog. Structures				
		Small <100 nodes)	Medium (<1,000)	Large (>1,000 nodes)	Complex (sparse)	Complex (dense)	Layered/K-Partite	Trees	Few (<5)	Several (≥5)	Homog. (1 type)	Hetero. (>1 type)	Few (<3)	Several (≥3)	Homog. (1 type)	Hetero. (>1 type)	Single node/edge	Neighbors	Paths	Clusters	Entire/sub network
Node-Link Layouts	On-node/edge encoding	3	2	1	3	1	3	3	2	1	3	2	2	1	3	1	3	3	2	2	2
	Attr.-driven faceting	3	1	1	3	1	3	1	3	1	3	3	2	1	2	1	3	2	1	1	1
	Attr.-driven positioning	3	1	1	3	1	1	1	3	1	3	1	2	1	2	1	3	2	1	1	2
Tabular Layouts	Adjacency matrix	3	1	1	2	3	2	1	2	3	3	2	3	2	3	2	3	3	1	3	2
	Quilts	3	1	1	3	1	3	3	3	3	3	3	3	3	3	2	3	3	2	2	2
	BioFabric	3	1	1	3	3	2	1	3	3	3	3	3	3	3	3	3	1	1	1	2
Implicit	Inner nodes & leaves	3	2	1	0	0	0	3	3	1	3	1	0	0	0	0	3	3	3	0	3
	Leaves	3	2	2	0	0	0	3	3	1	3	1	0	0	0	0	3	2	1	0	3
View Operations	Juxtaposed	3	2	1	3	1	3	3	3	3	3	3	3	3	3	3	2	1	1	2	2
	Integrated	3	2	1	3	1	3	3	3	3	3	3	2	2	3	3	3	3	3	1	2
	Overloaded	3	2	1	3	1	3	3	3	1	3	1	1	1	1	1	3	3	2	3	2

0 Does *not* support

1 Supports poorly

2 Supports

3 Optimized for

LAYOUTS
VIEW OPERATIONS
LAYOUT OPERATIONS
DATA OPERATIONS
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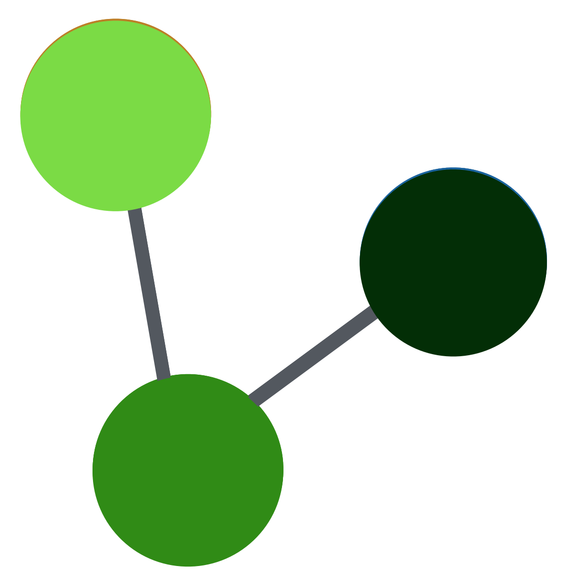
LAYOUTS

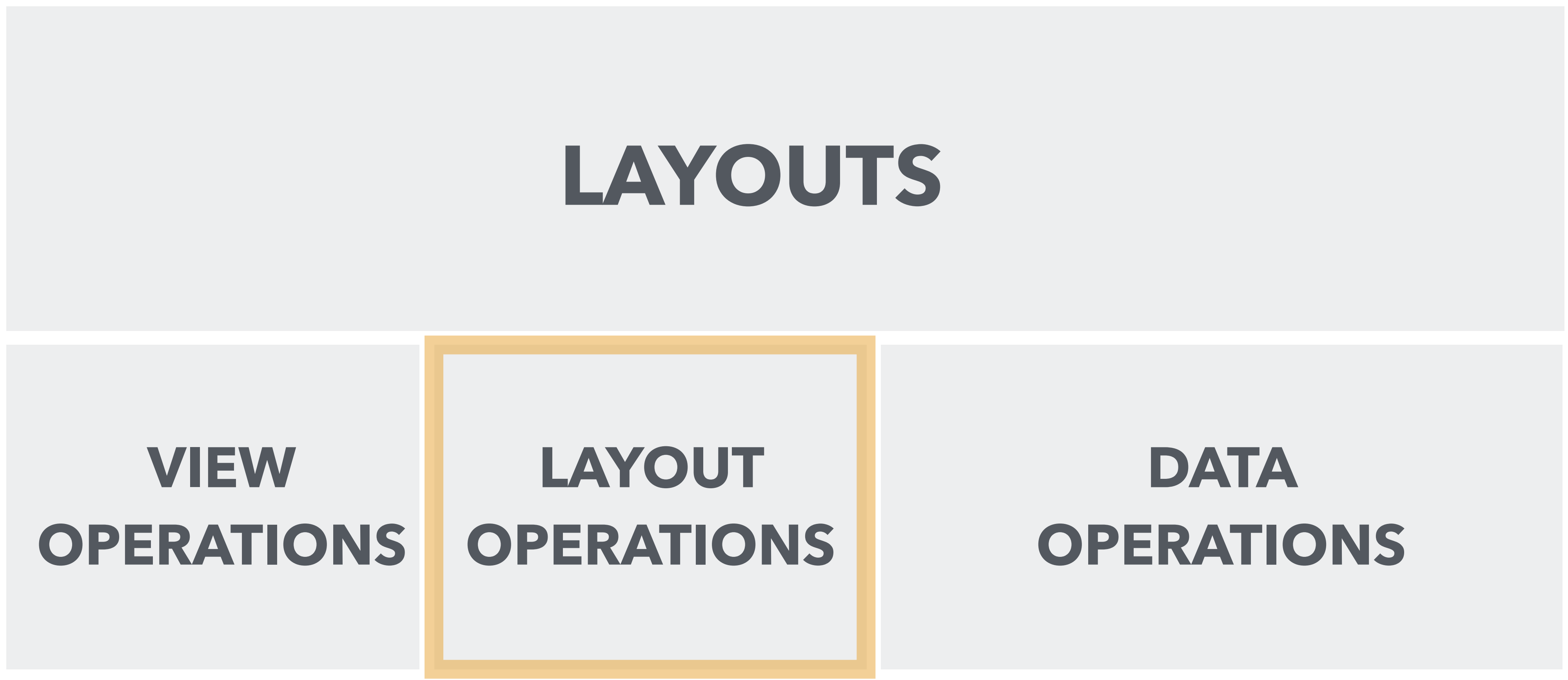
VIEW OPERATIONS

LAYOUT OPERATIONS

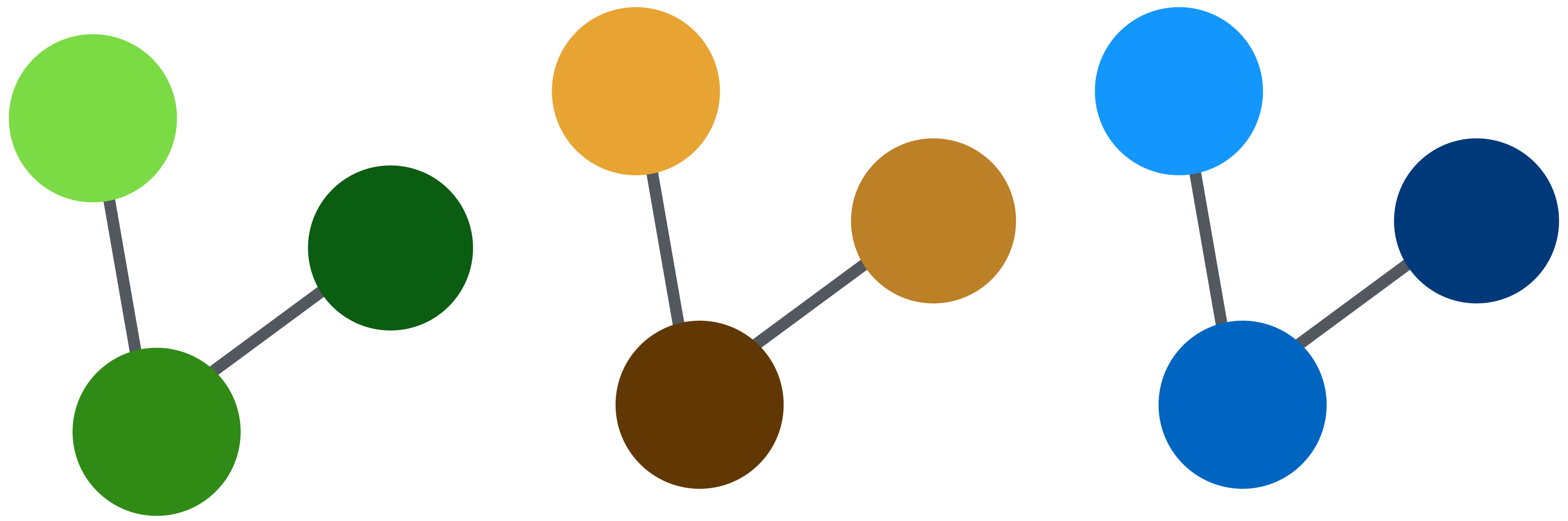
DATA OPERATIONS

Node-Link Diagram with on-node encoding





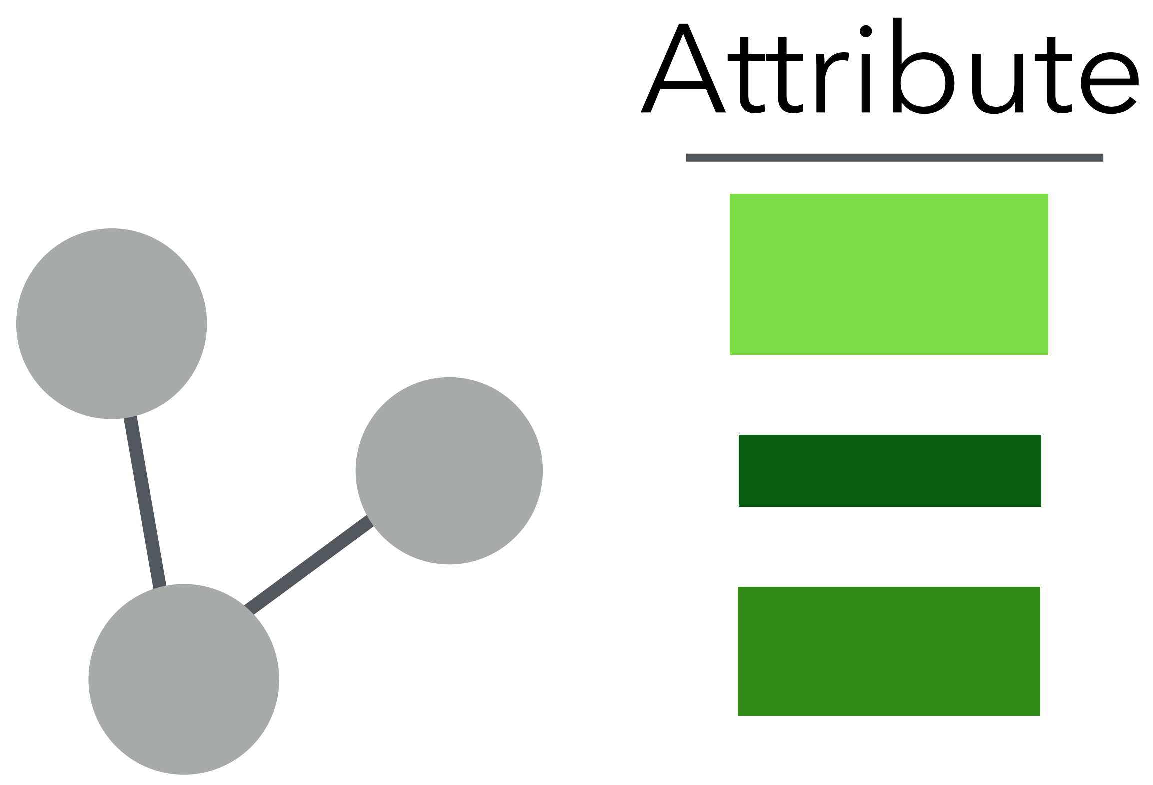
Small Multiples



LAYOUTS

VIEW OPERATIONS | LAYOUT OPERATIONS | DATA OPERATIONS

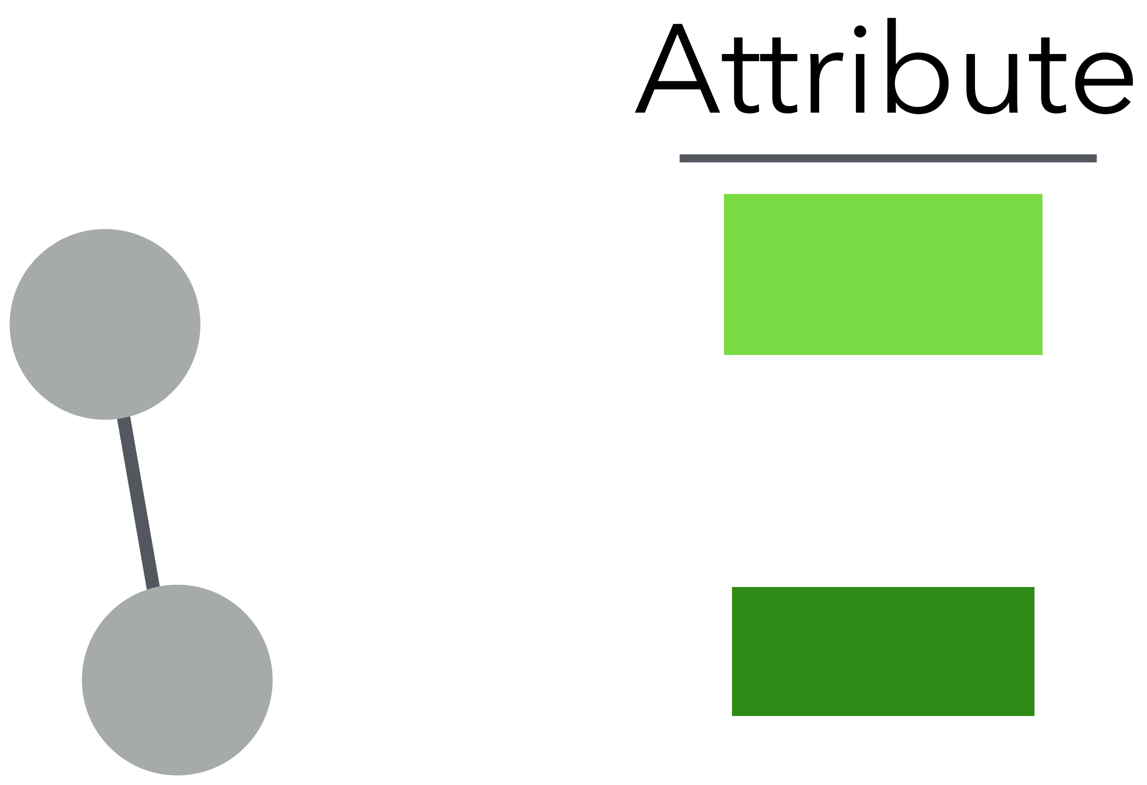
Juxtaposed Views

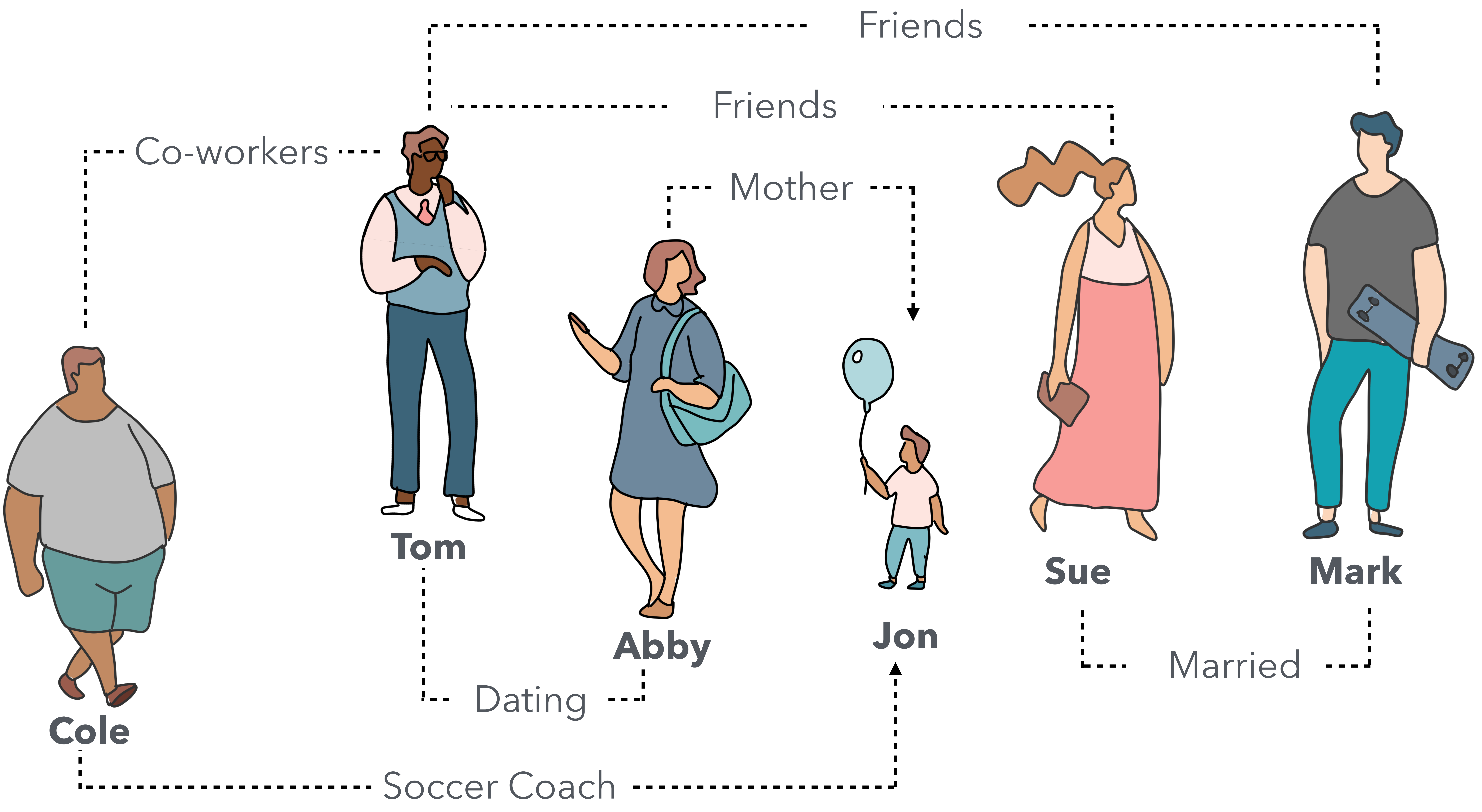


LAYOUTS

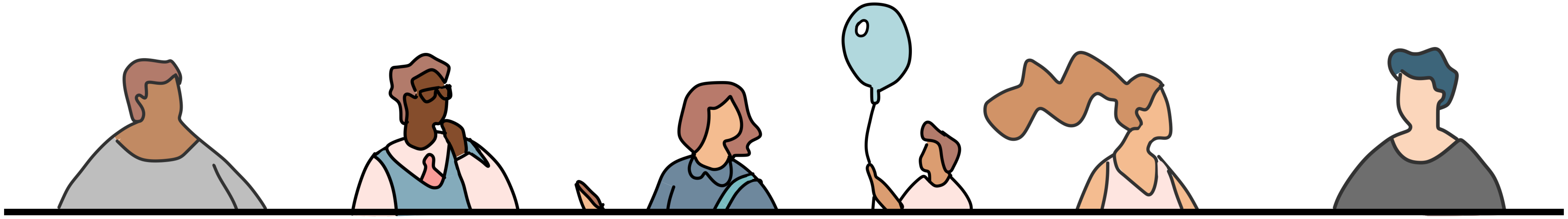
VIEW OPERATIONS | LAYOUT OPERATIONS | DATA OPERATIONS

Filter Data

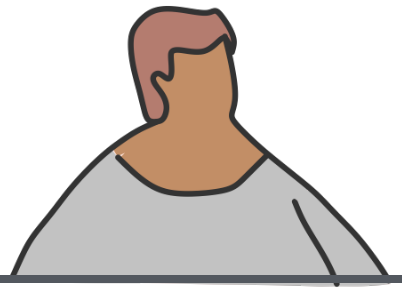
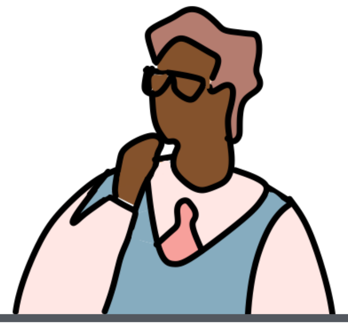
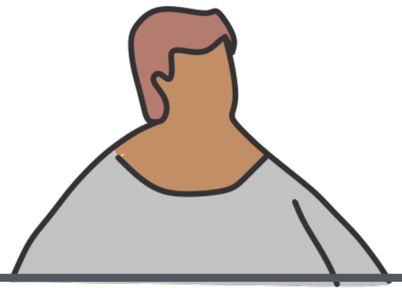
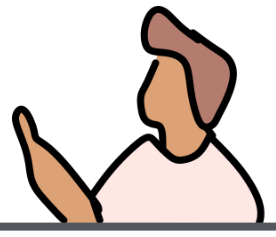
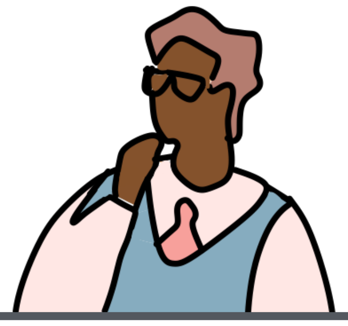
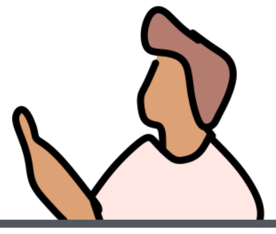
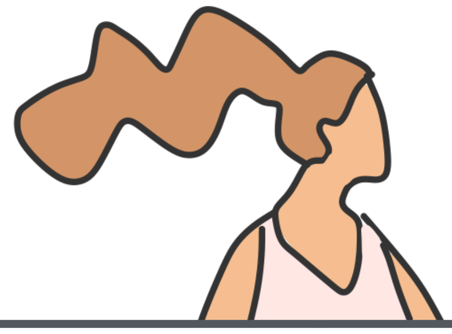
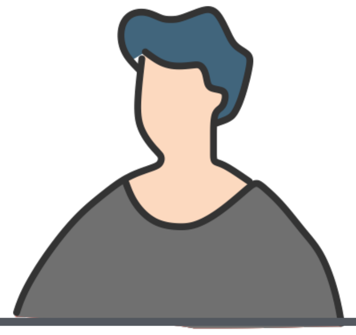
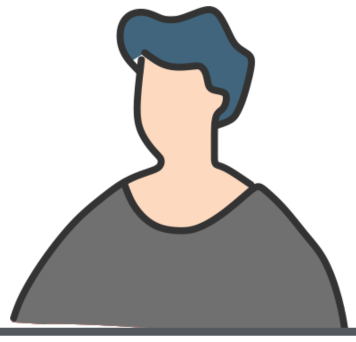




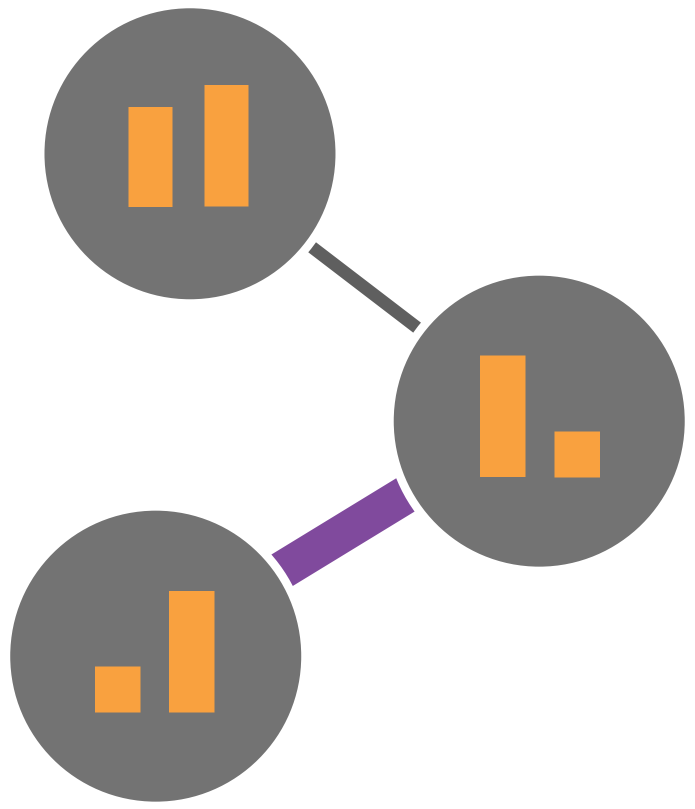
Friends
Friends
Co-workers
Mother
Tom
Abby
Jon
Sue
Mark
Cole
Dating
Married
Soccer Coach

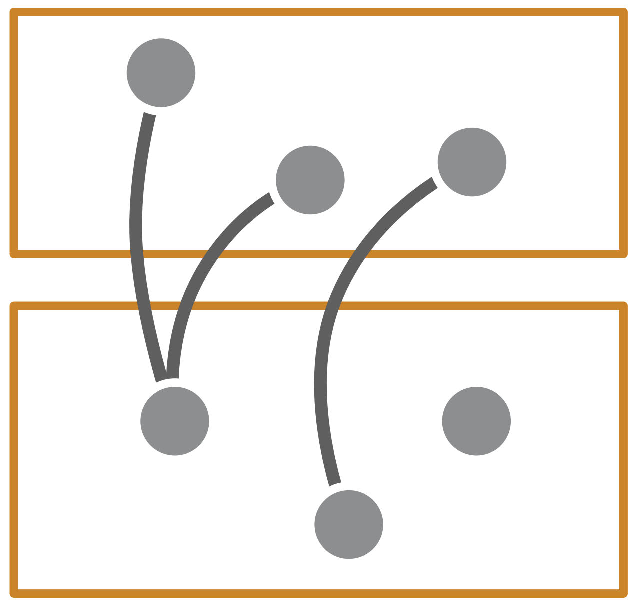


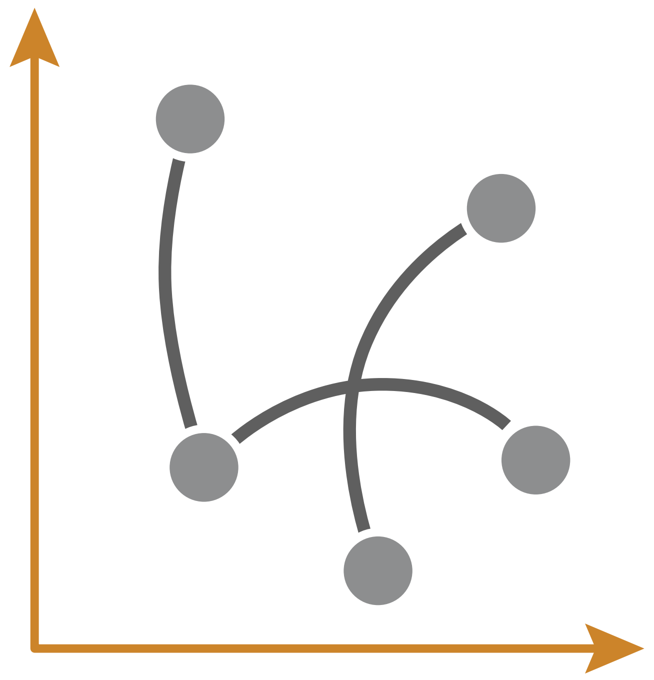
Name	Cole	Tom	Abby	Jon	Sue	Mark
Beverage	Port	Beer	Port	Coke	Coke	Beer
Day 1	1	0	4	3	3	5
Day 2	0	2	5	3	5	5
Day 3	4	1	2	2	4	3

Source	Target	Type	Duration
		Co-workers	3 years
		Soccer Coach	2 years
		Dating	1 year
		Mother / Son	7 years
		Friends	12 years
		Friends	3 years
		Married	6 years

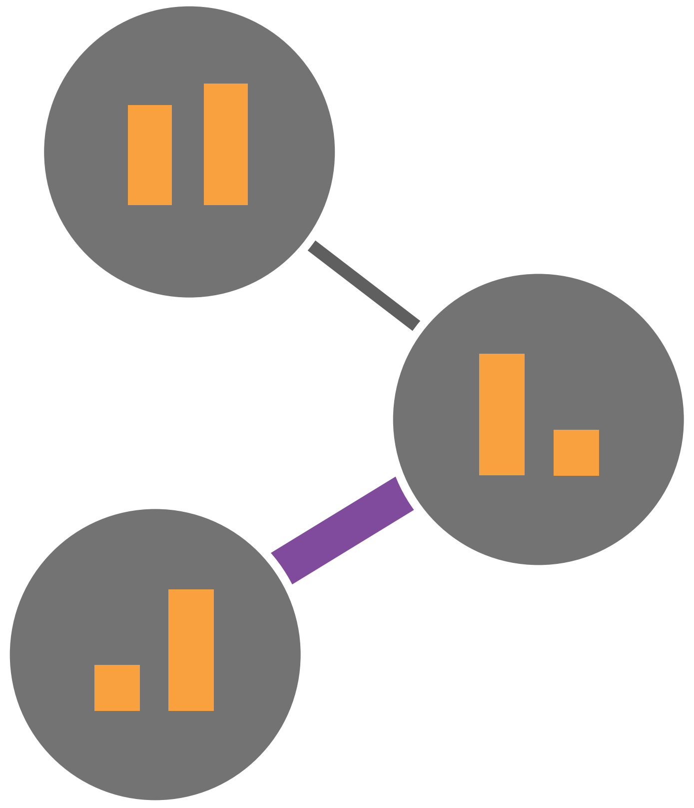
Node-Link Layouts



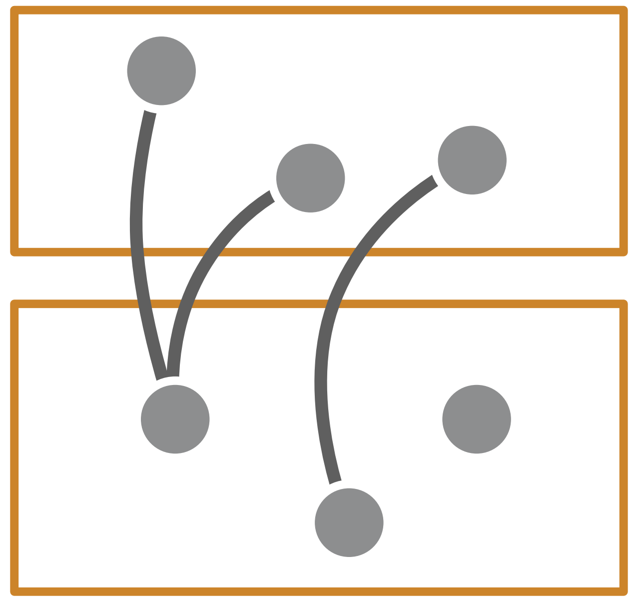


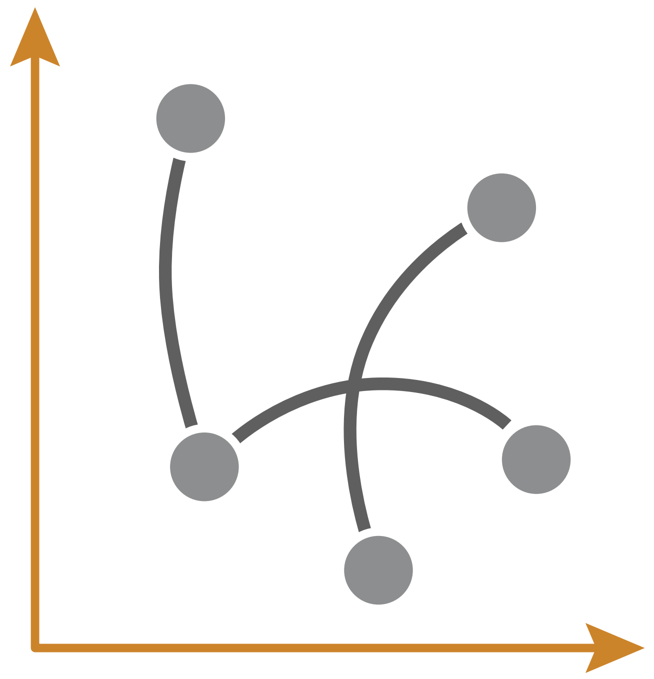


Topology Driven Layout

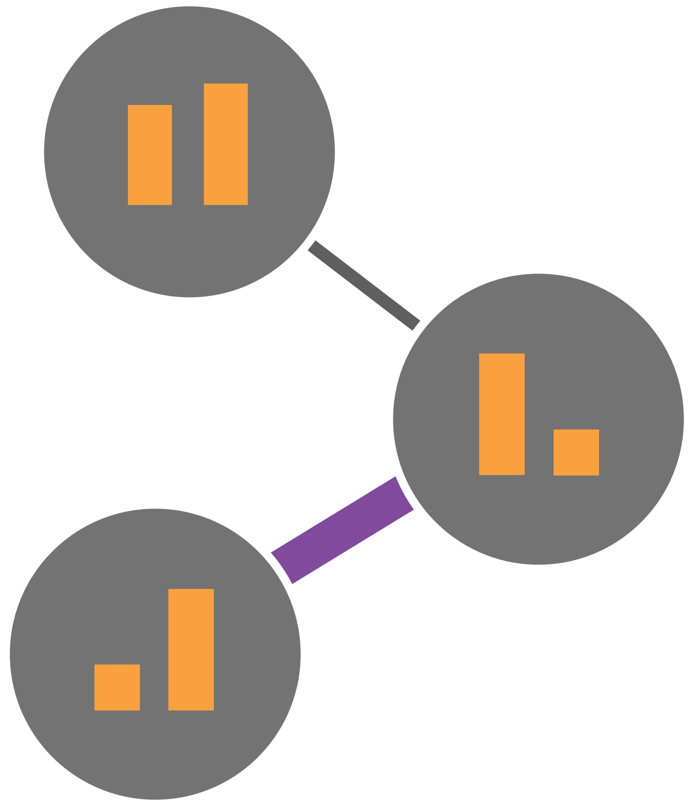


Attribute Driven Layouts



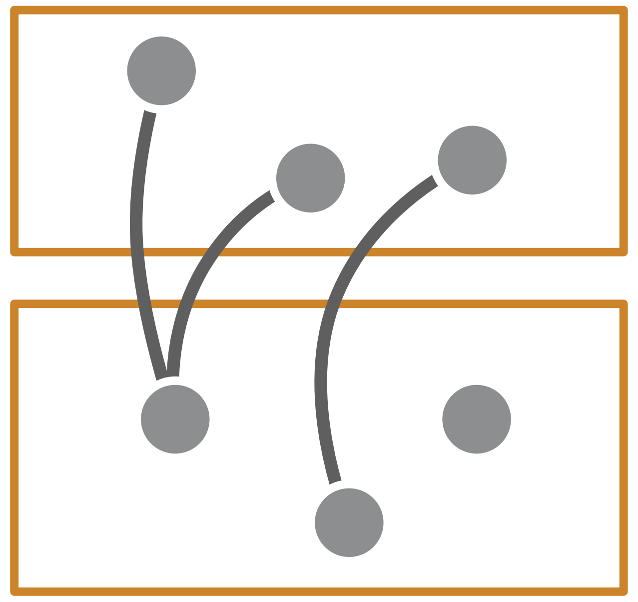


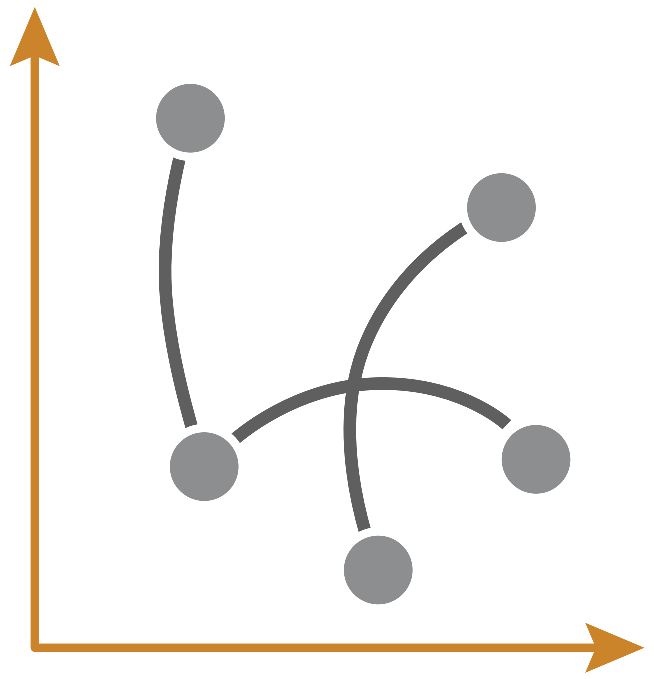
Topology Driven Layout



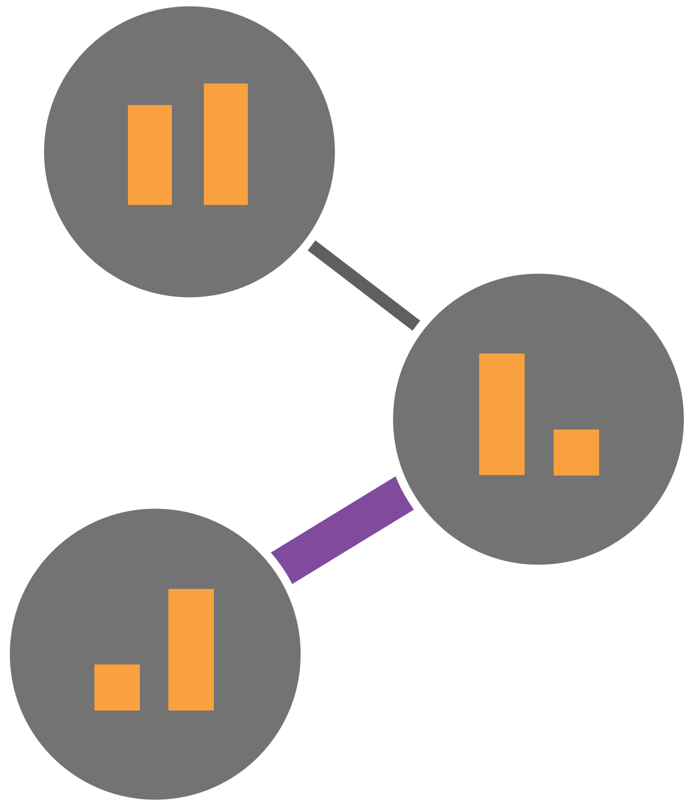
On-Node / On-Edge
Encoding

Attribute Driven Layouts



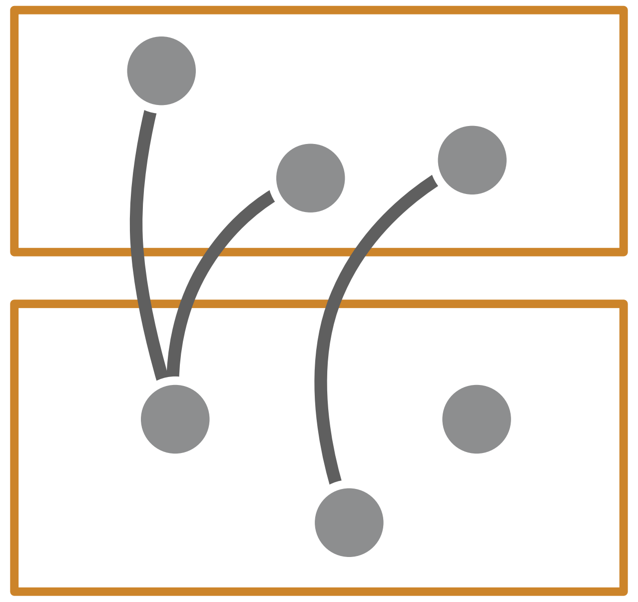


Topology Driven Layout

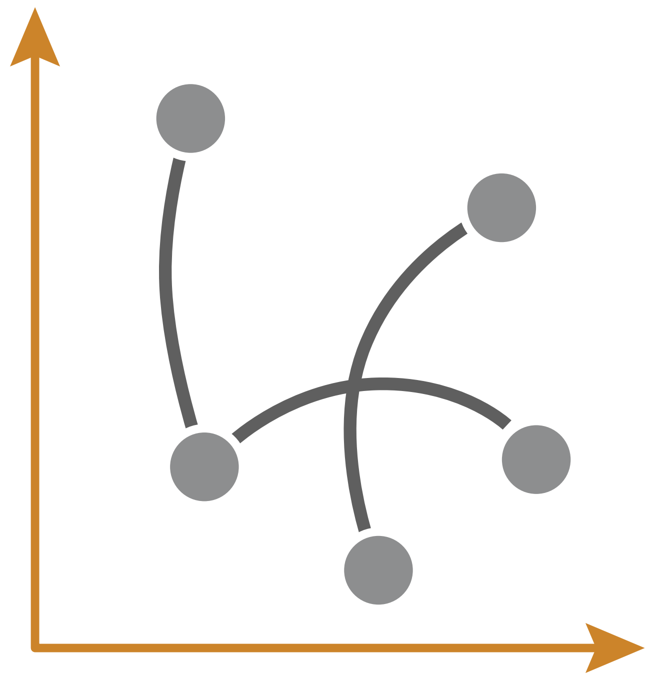


On-Node / On-Edge
Encoding

Attribute Driven Layouts

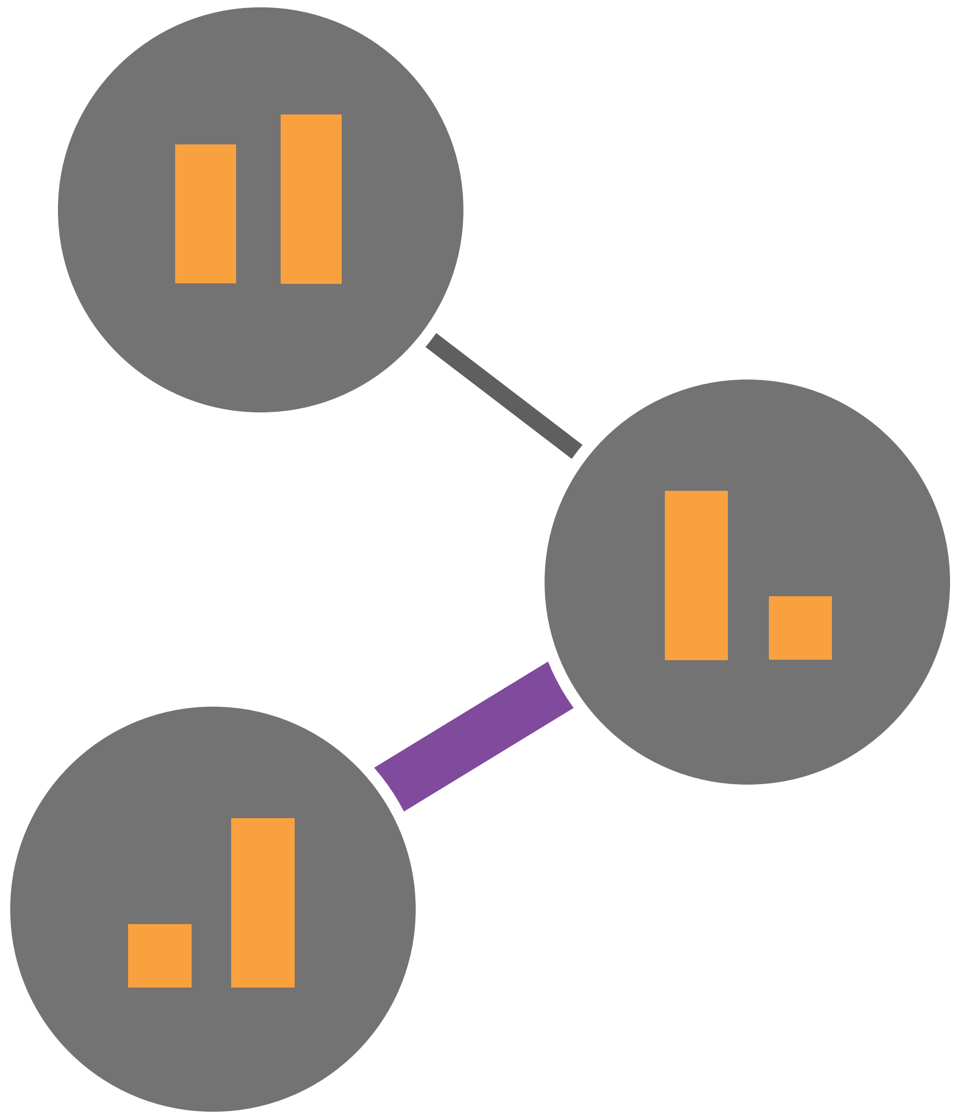


Attribute-Driven
Faceting

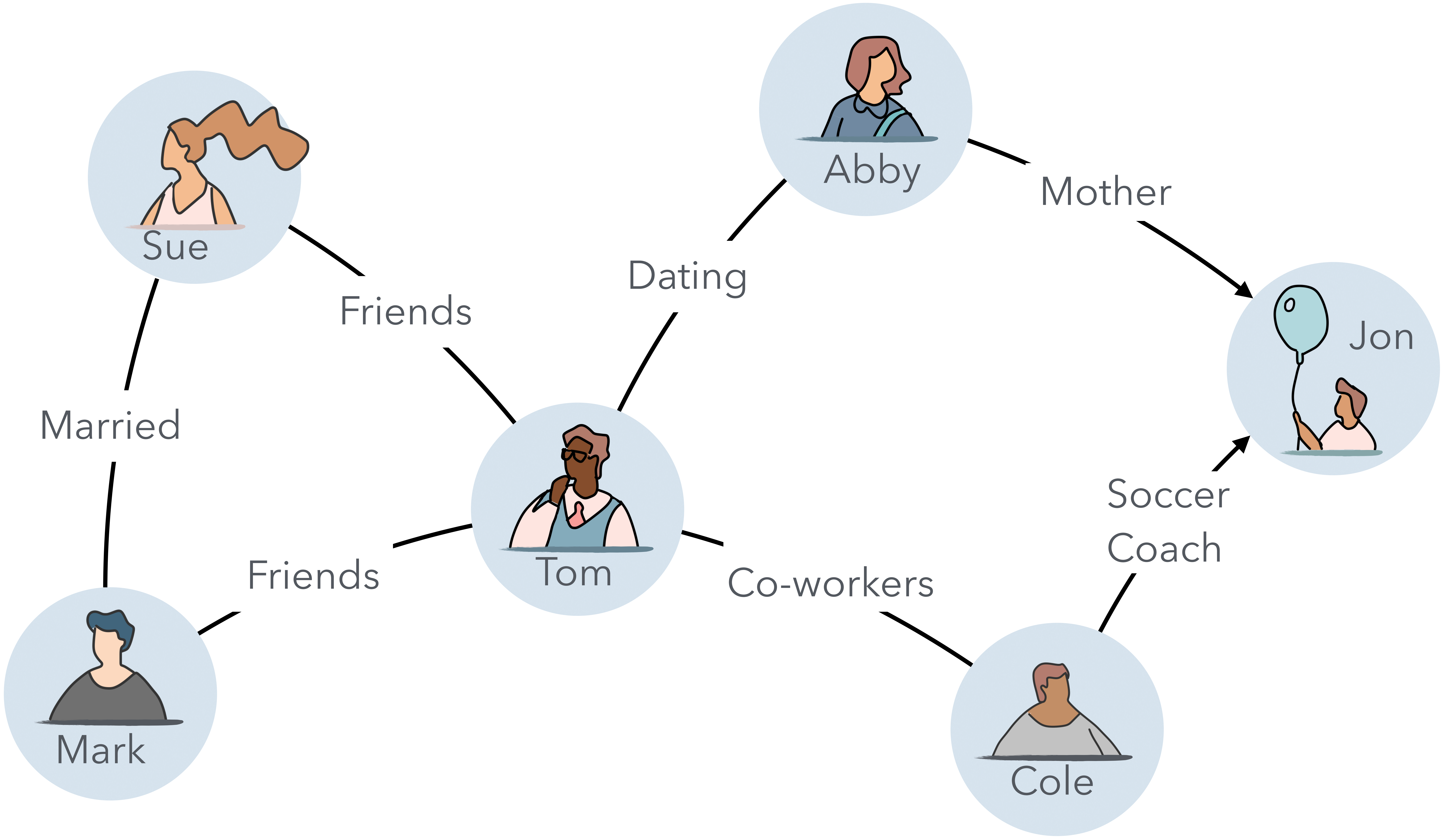


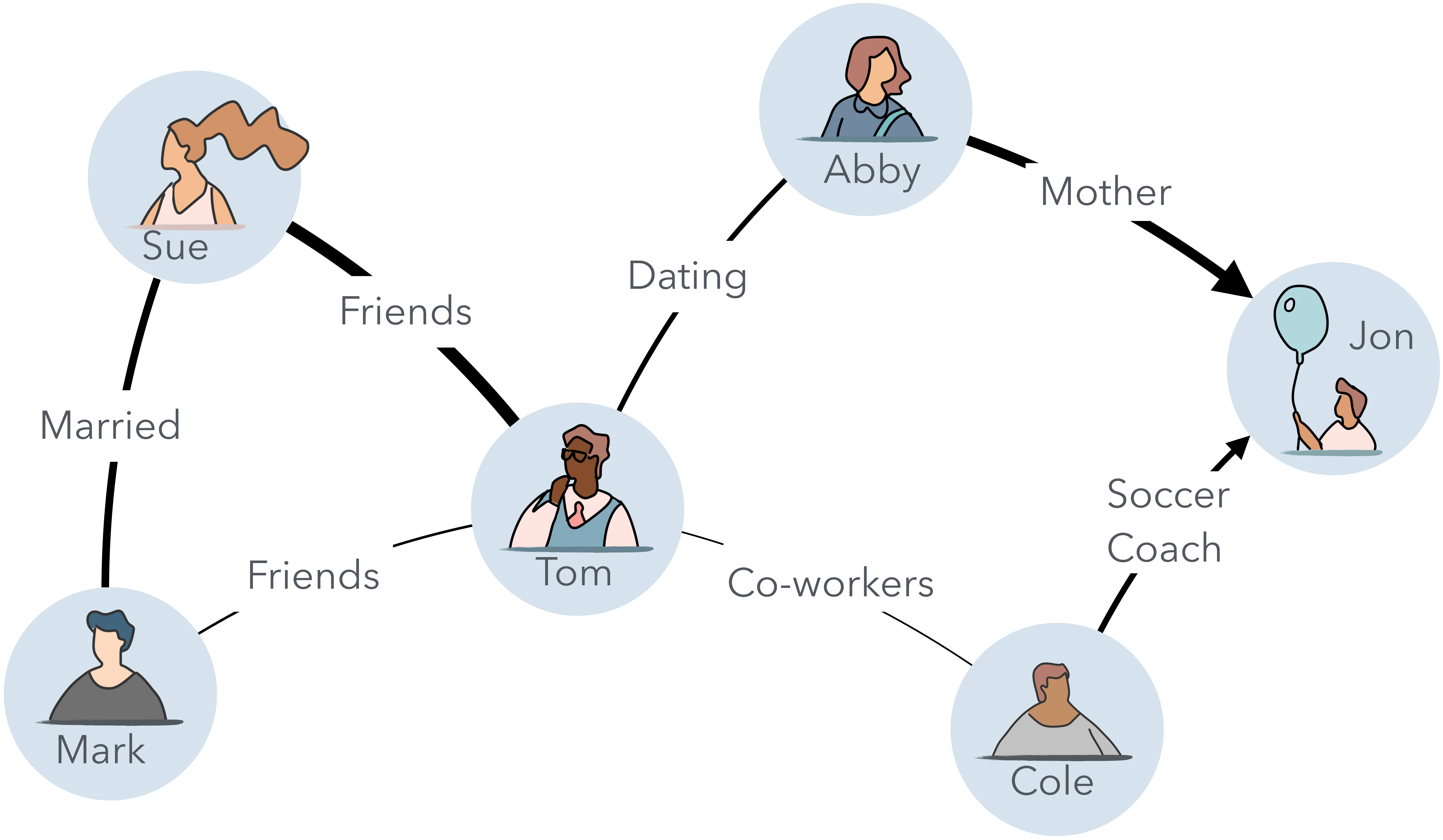
Attribute-Driven
Positioning

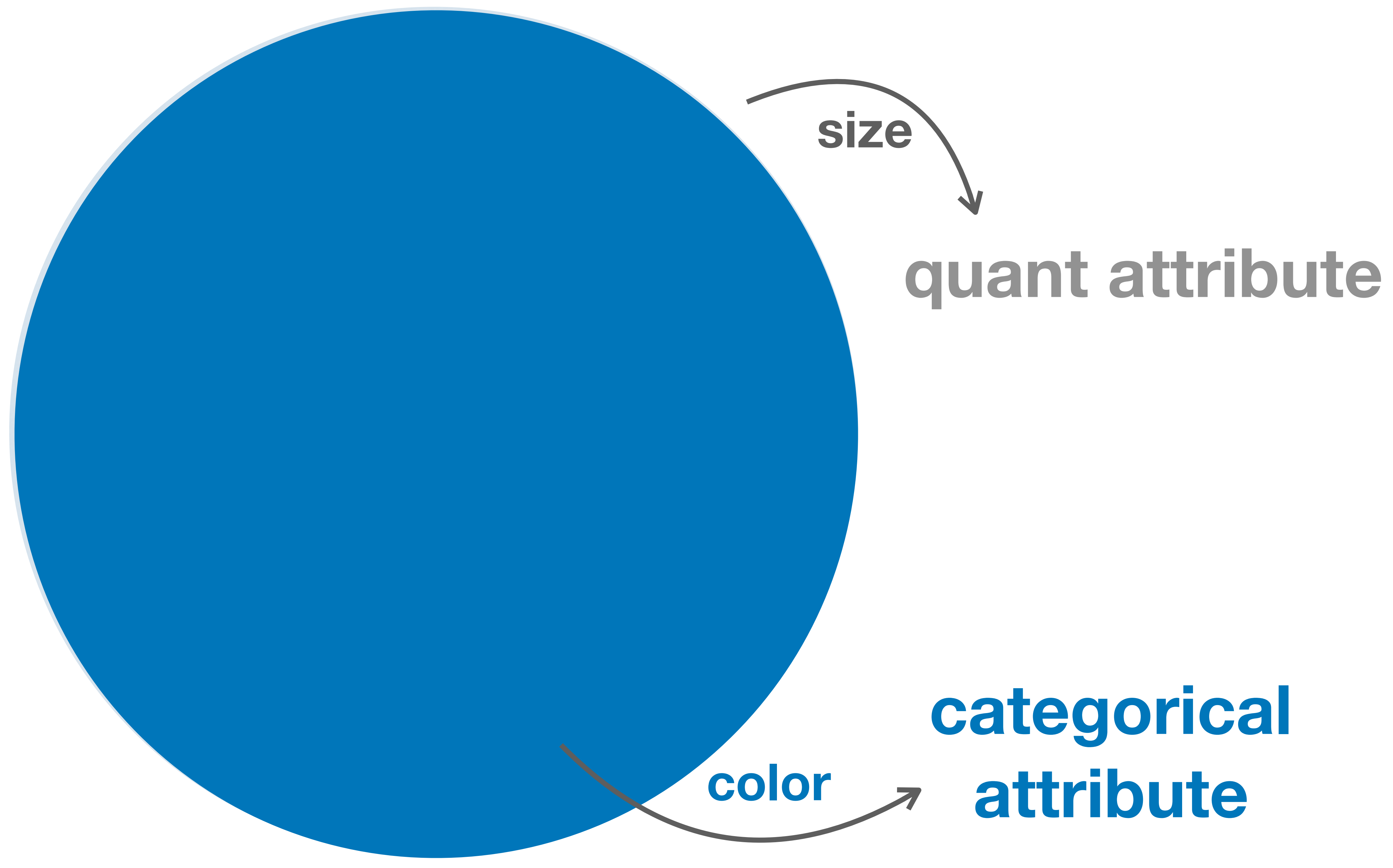
On-Node / On-Edge Encoding

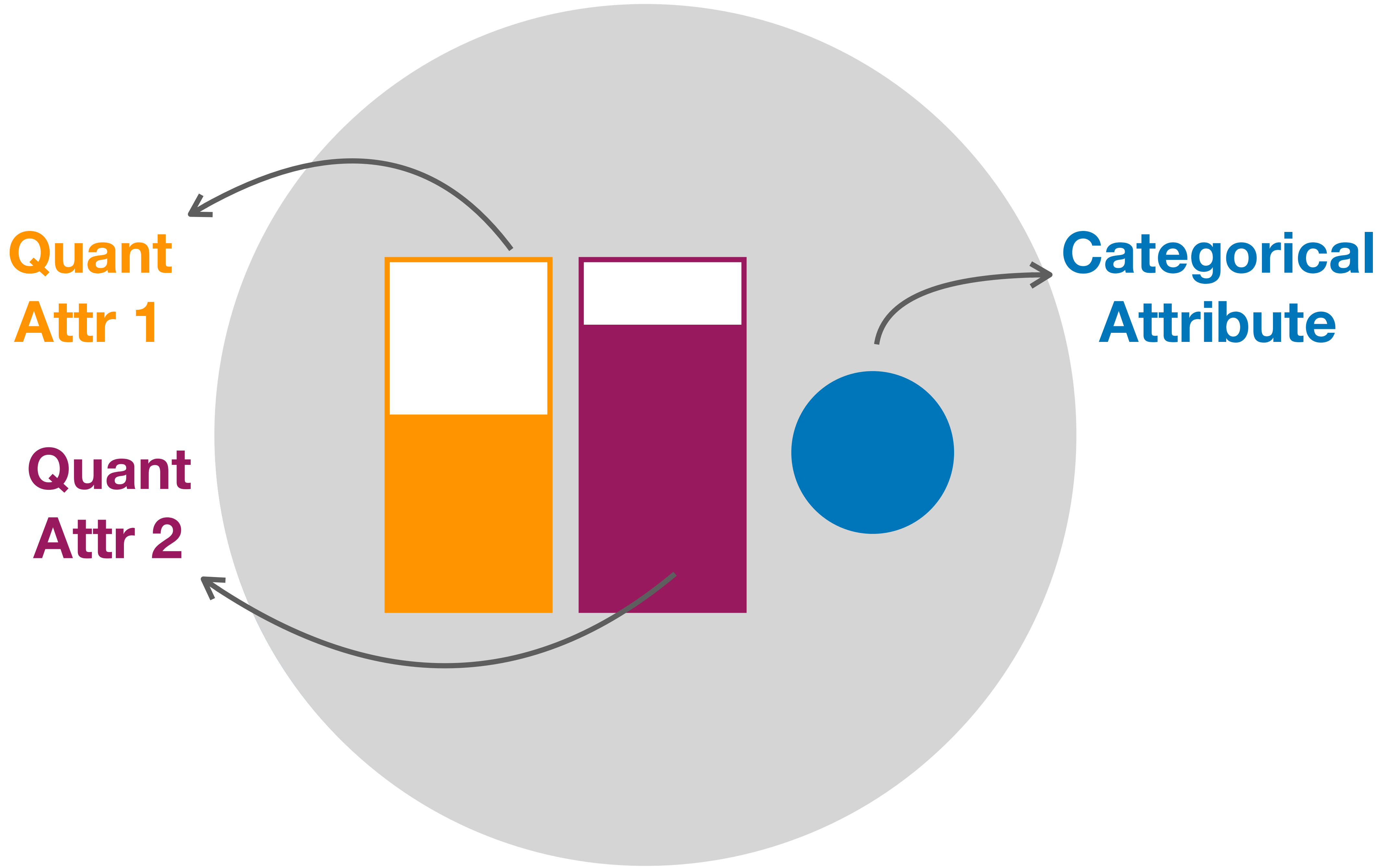


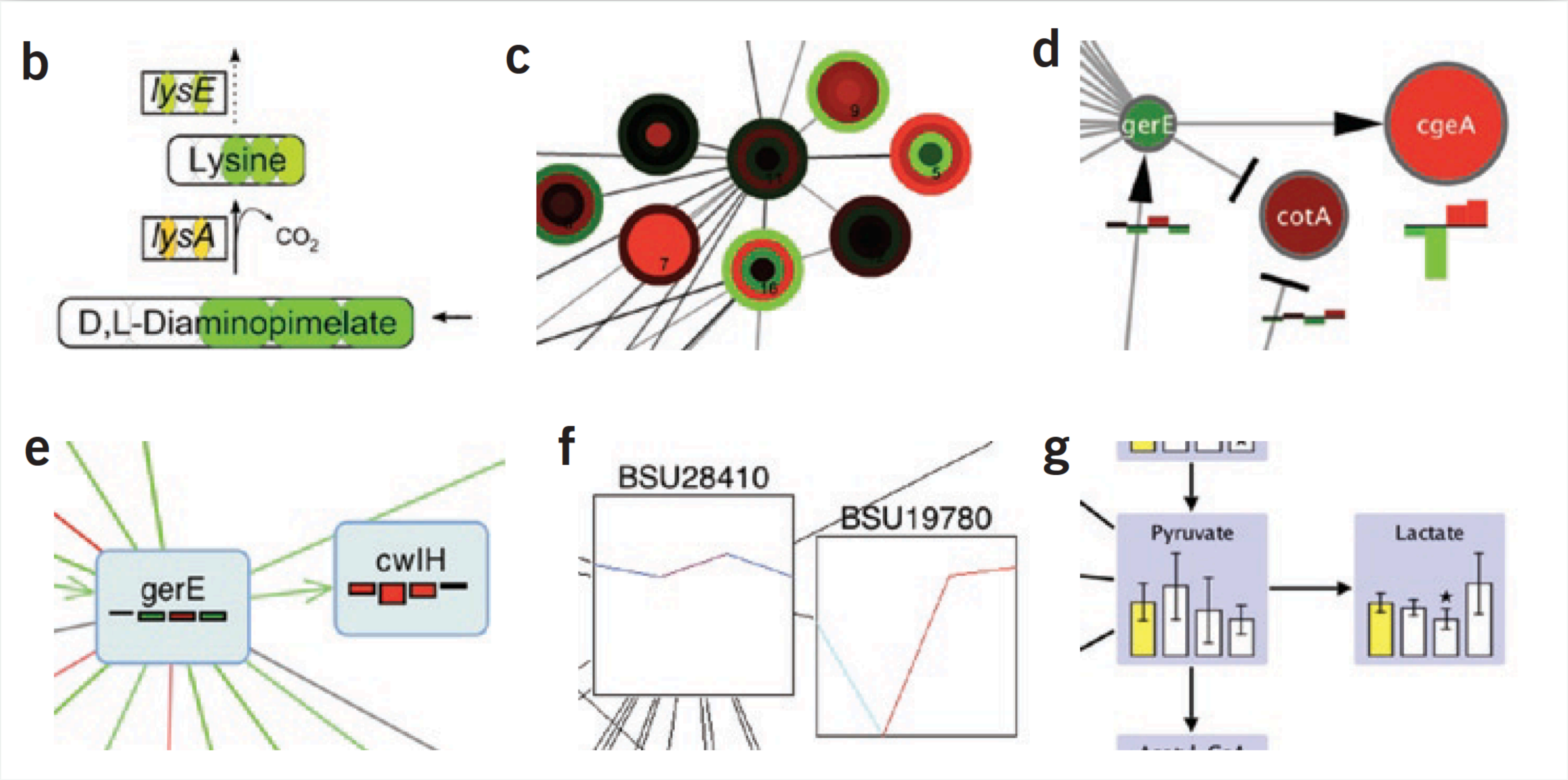

Mark
Sue
Tom
Abby
Cole
Jon


Sue
Abby
Mother
Dating
Friends
Jon
Married
Tom
Soccer
Coach
Friends
Co-workers
Mark
Cole

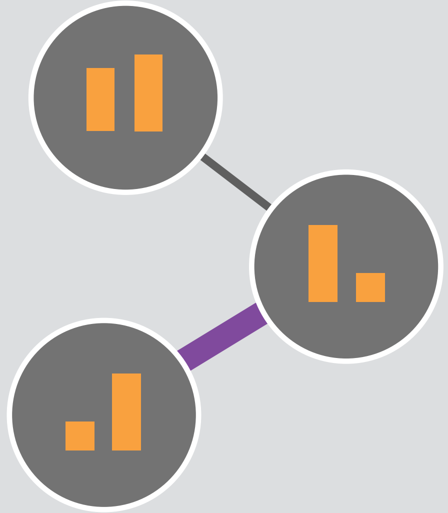

Sue
Friends
Abby
Mother
Dating
Jon
Married
Tom
Friends
Soccer
Coach
Co-workers
Mark
Cole


size
quant attribute
color
categorical
attribute

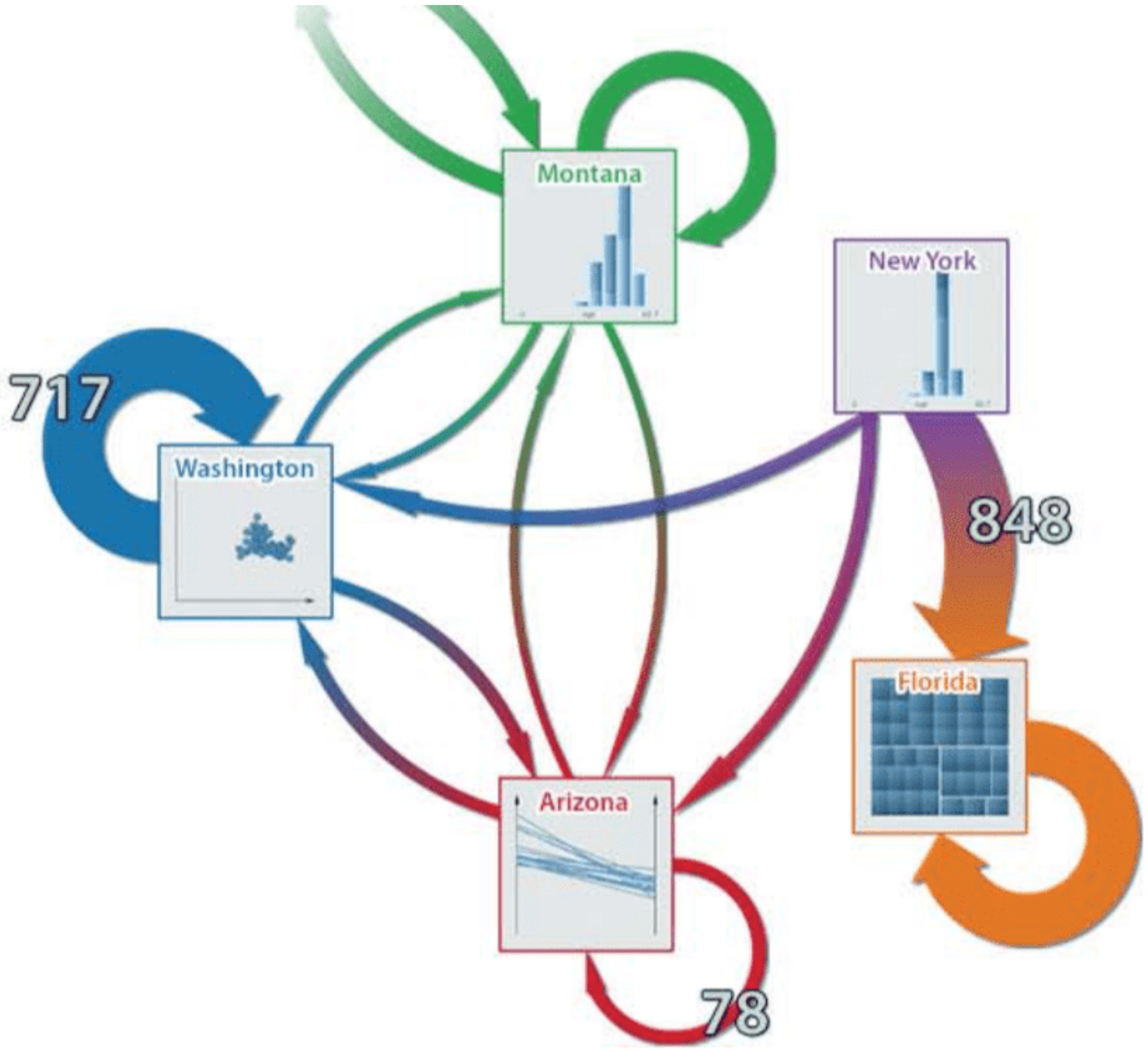

Quant
Attr 1
Quant
Attr 2
Categorical
Attribute



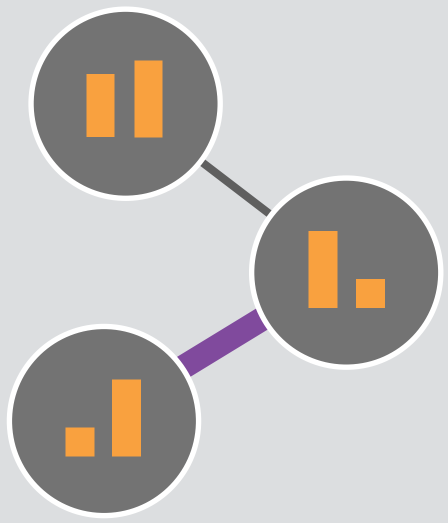
Gehlenborg et al. 2010



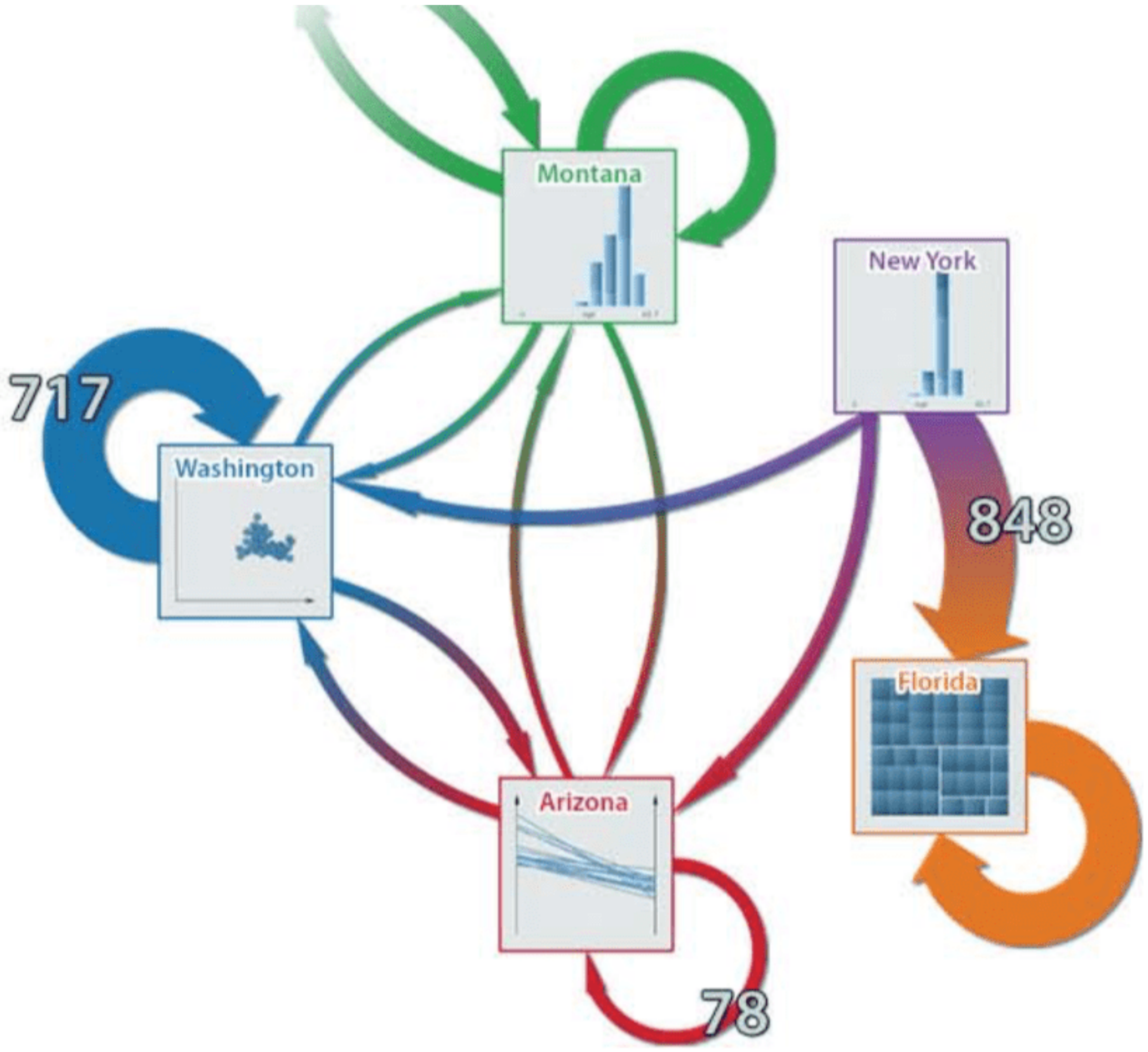
On-Node / On-Edge Encoding



Elzen and Wijk, 2014

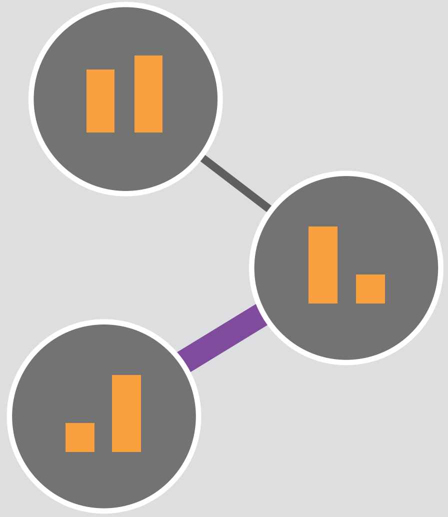


On-Node / On-Edge Encoding

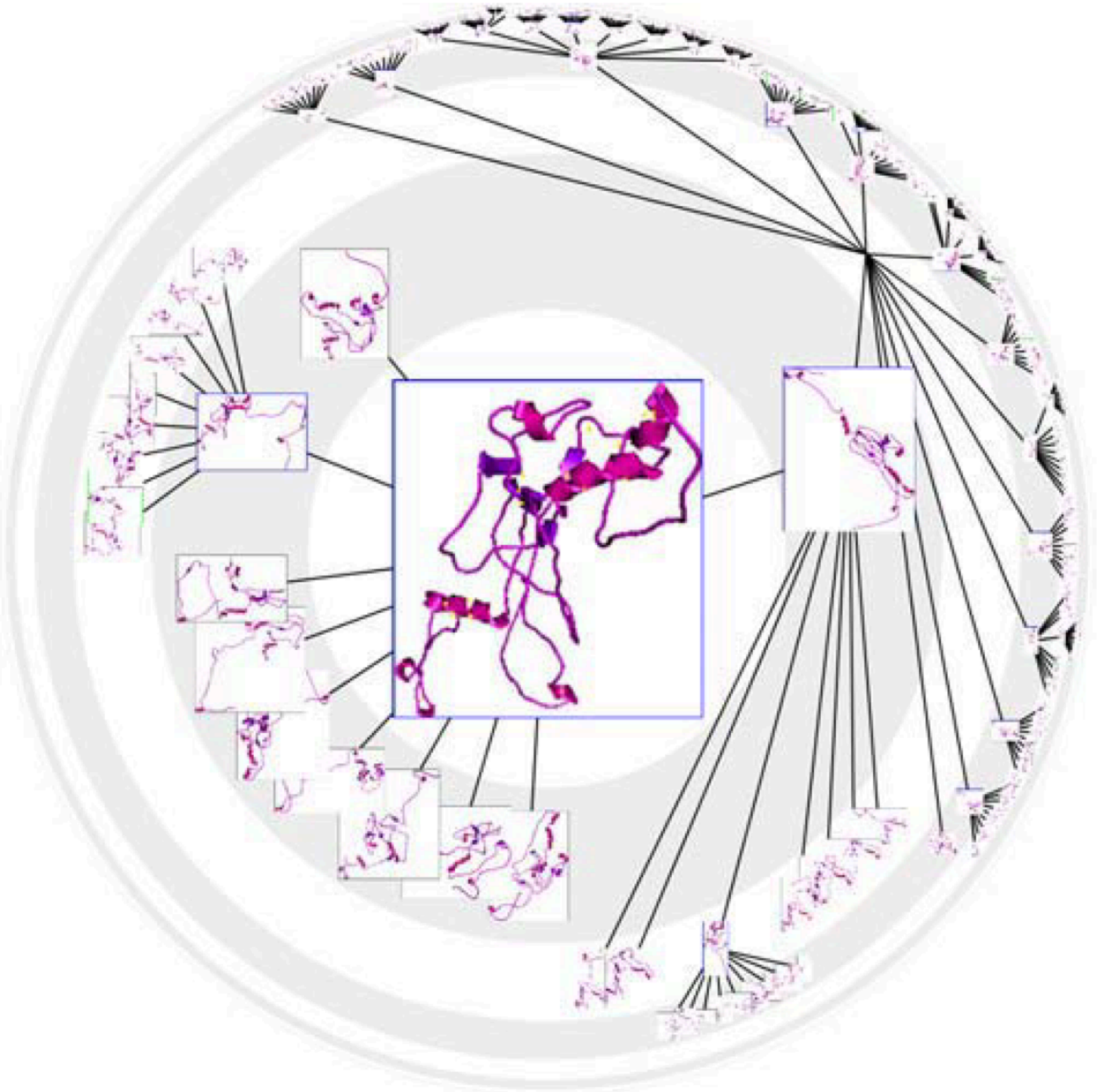


Elzen and Wijk, 2014

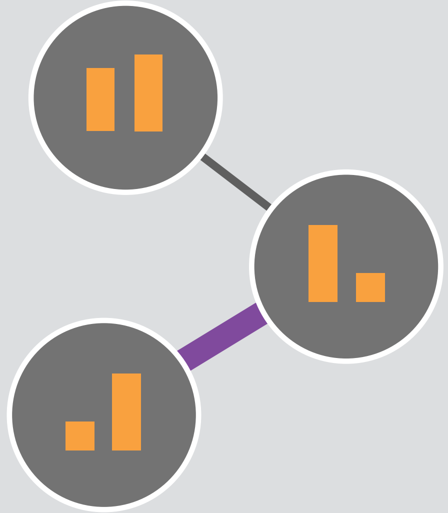
Aggregating Nodes/Edges



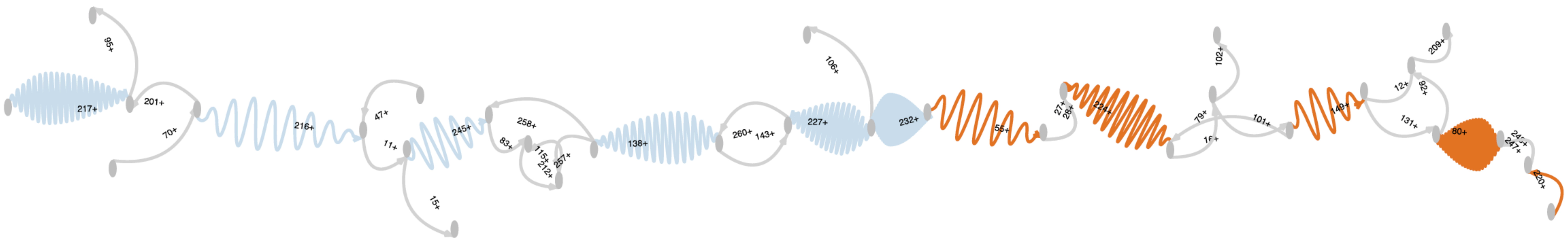
On-Node / On-Edge
Encoding



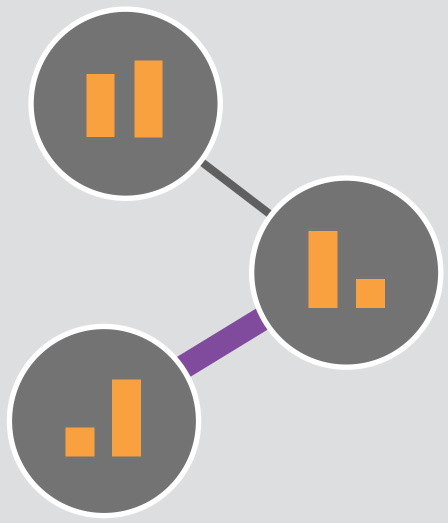
Jankun-Kelly and Ma, 2003



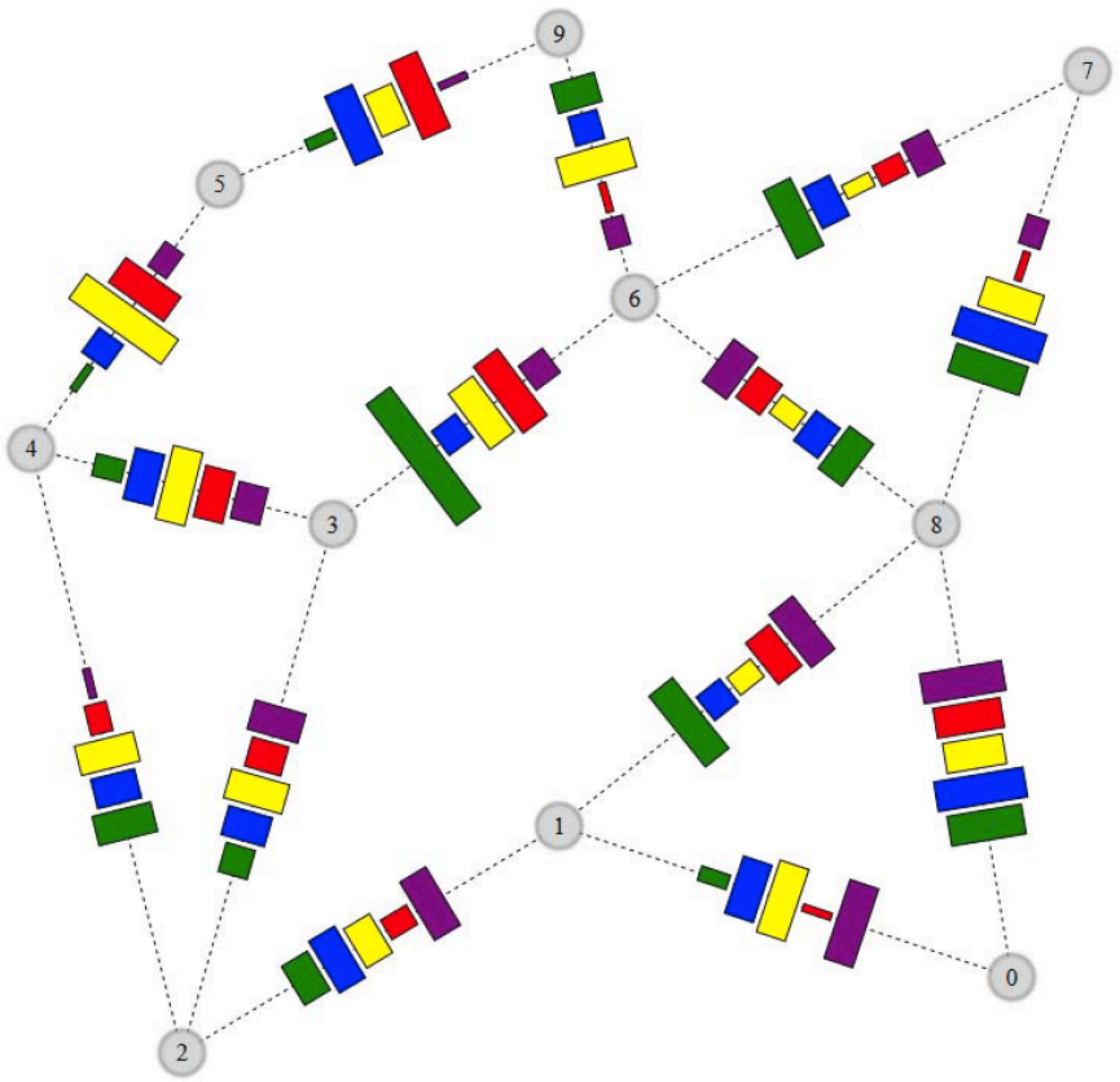
On-Node / On-Edge
Encoding

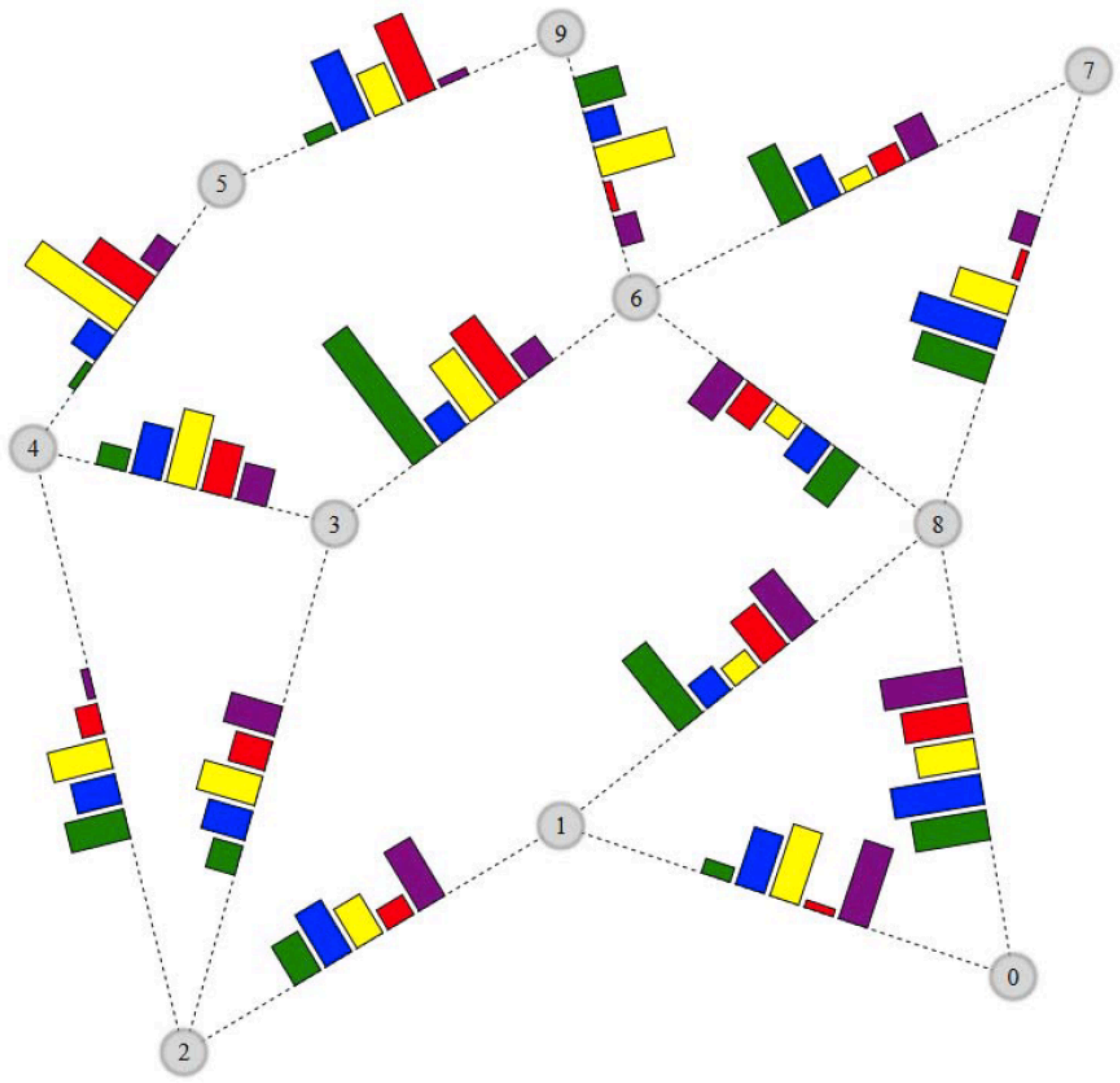


Nielsen, 2009

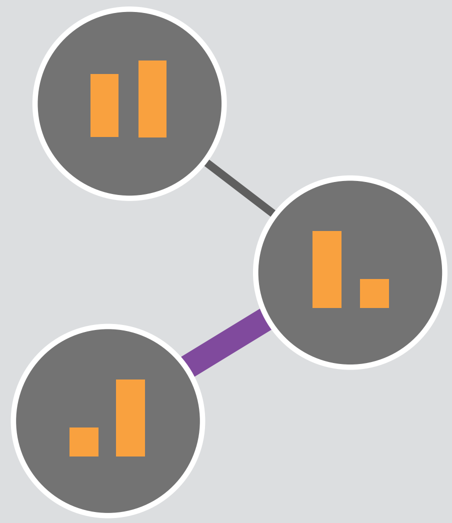


On-Node / On-Edge
Encoding

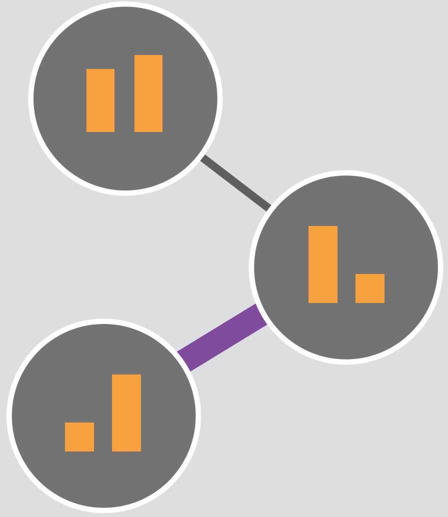




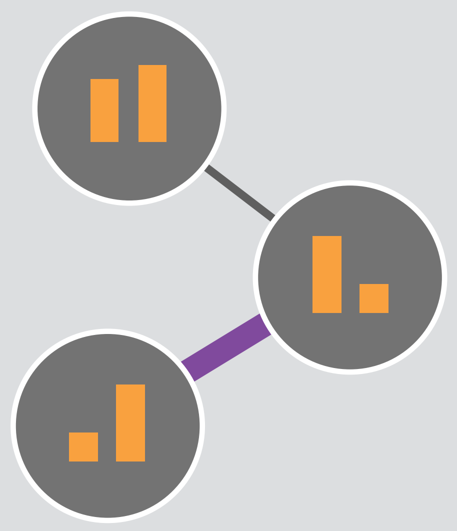
Schöffel et al, 2016



On-Node / On-Edge Encoding



On-Node / On-Edge Encoding



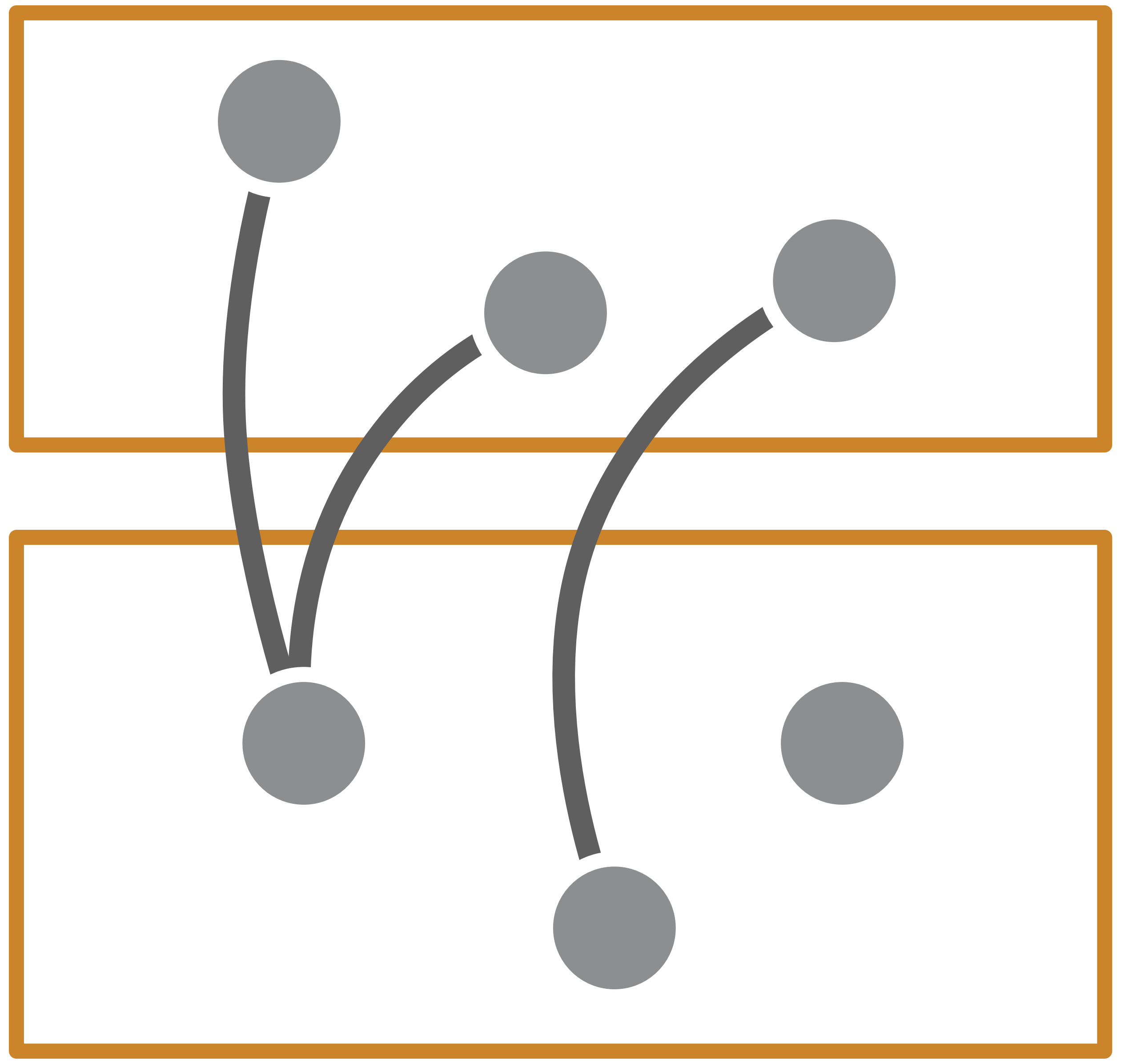
On-Node / On-Edge Encoding

Is easily understood by most users
Works well for all types of networks

Scalability.
Node size leaves little space to encode attributes.

Recommended for small networks when only a few (usually under five) attributes on the nodes are shown, or in combination with a zooming/filtering strategy

Attribute-Driven Faceting




Coca-Cola
classic

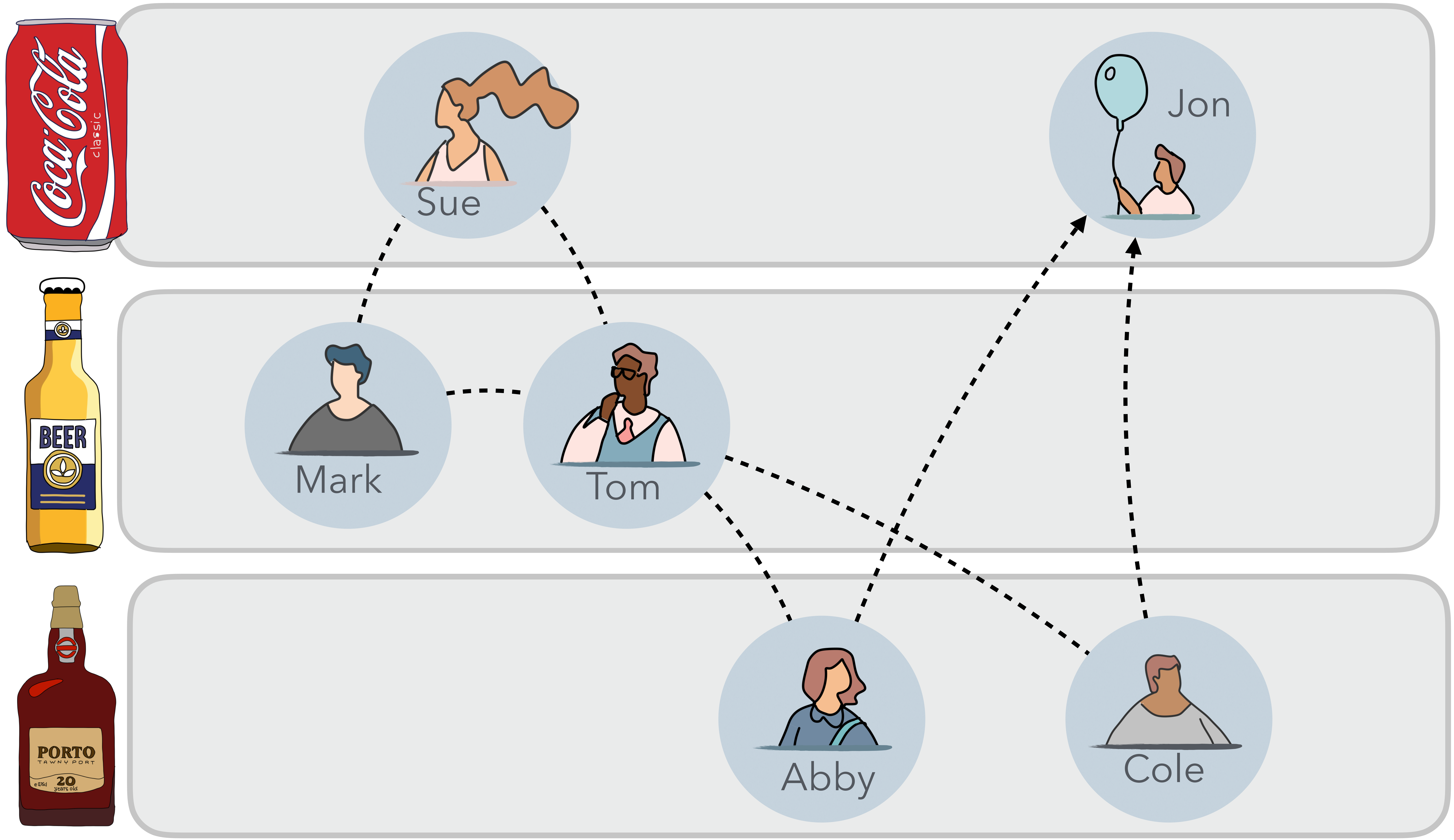
BEER

PORTO
TAWNY PORT
e 0,75cl
20
years old

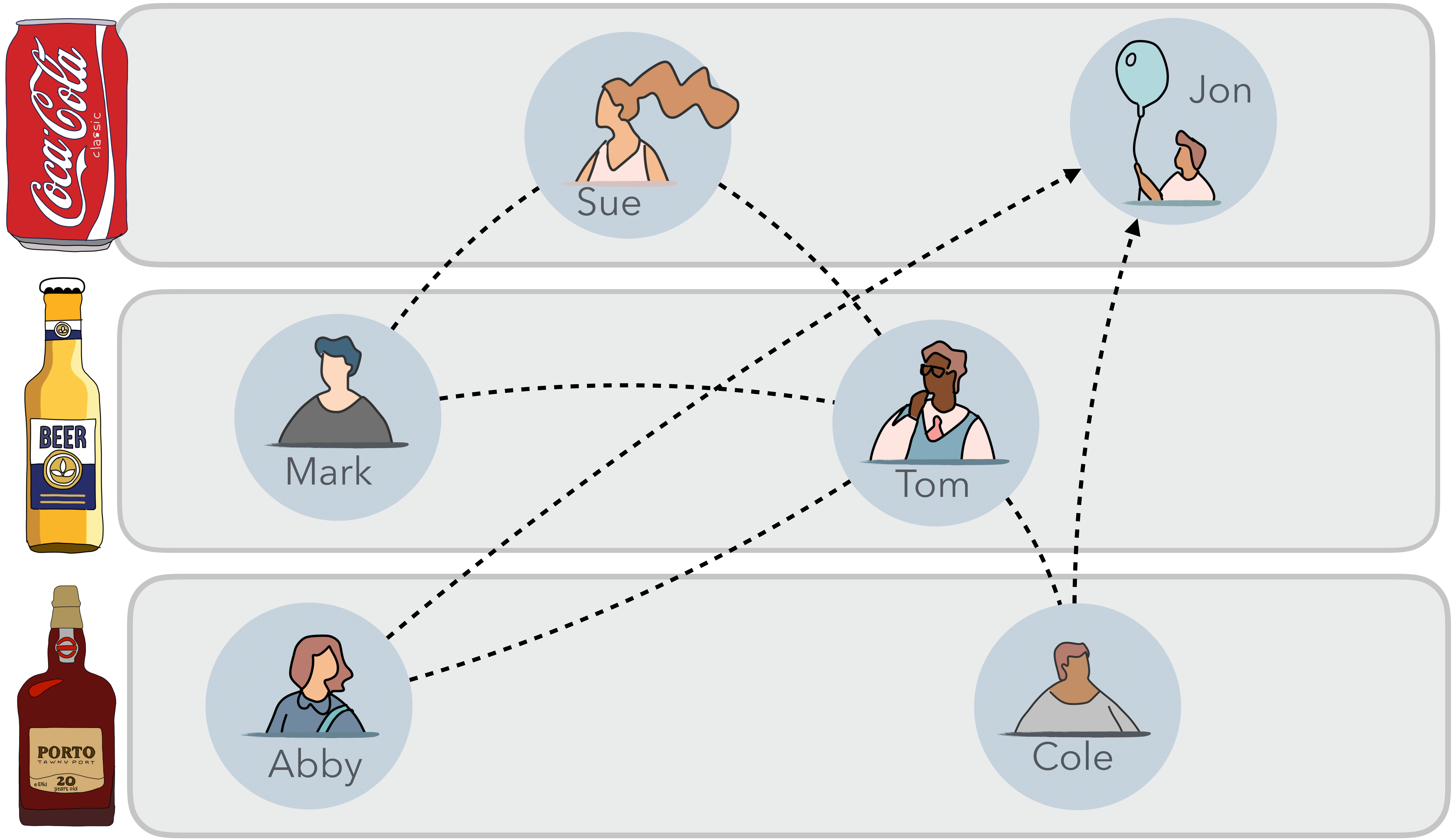

Coca-Cola
classic


BEER

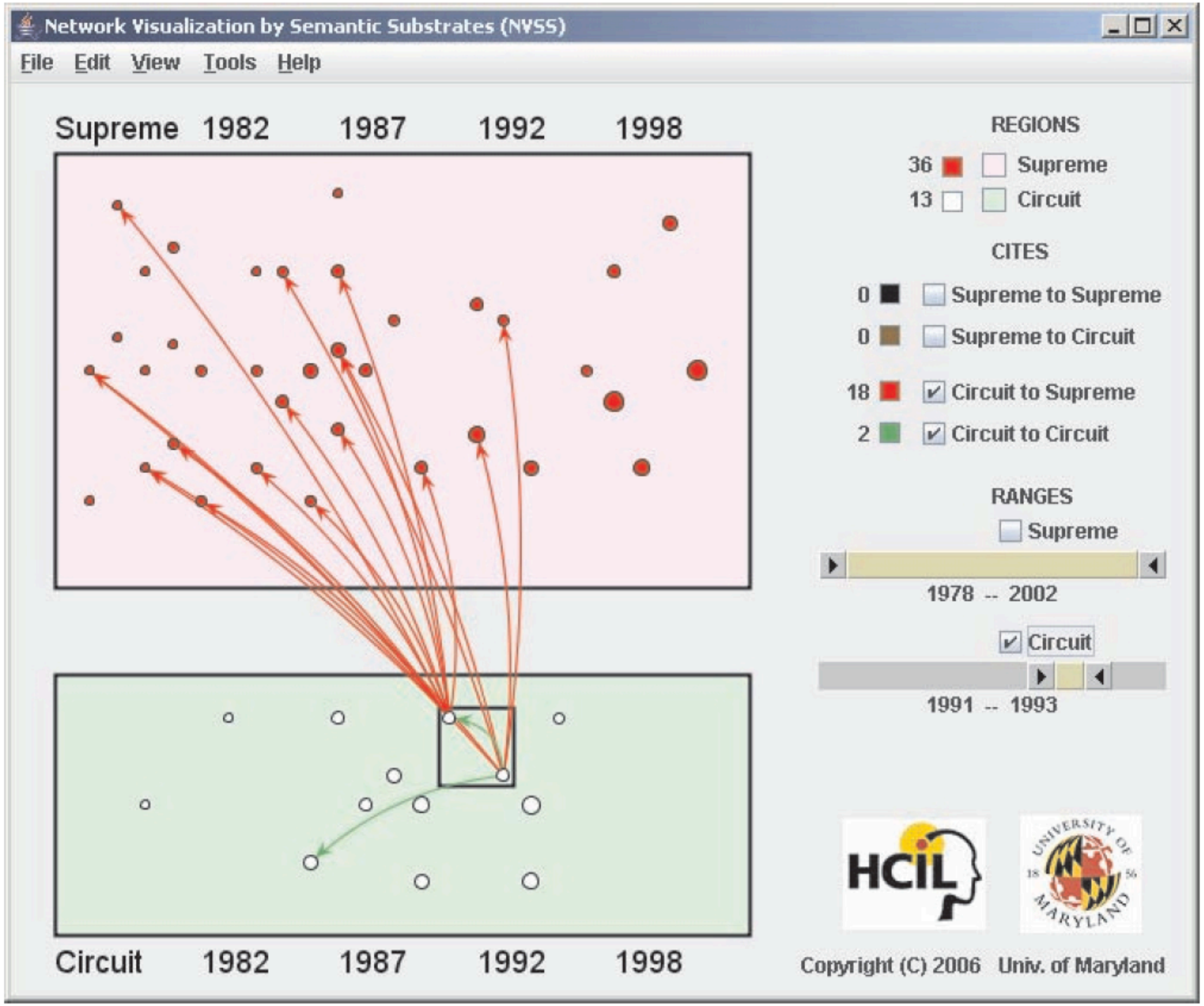

PORTO
TAWNY PORT
20
years old

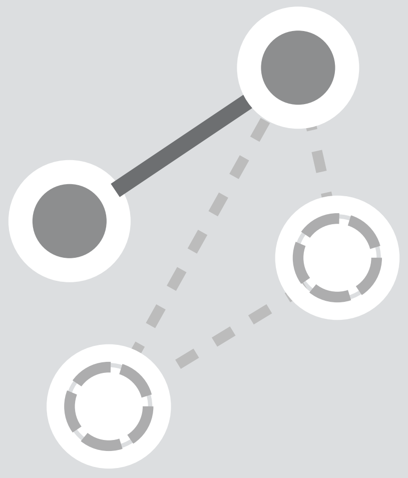


Coca-Cola classic
Sue
Jon
BEER
Mark
Tom
PORTO
TAWNY PORT
20
years old
Abby
Cole

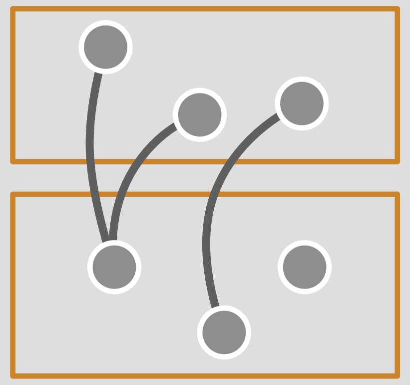

Coca-Cola
classic
BEER
PORTO
TAWNY PORT
20
years old
Sue
Jon
Mark
Tom
Abby
Cole

Semantic Substrates *Shneiderman and Aris, 2006*

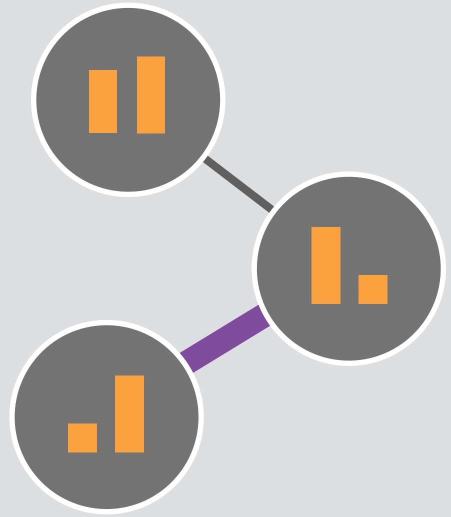




Querying and Filtering

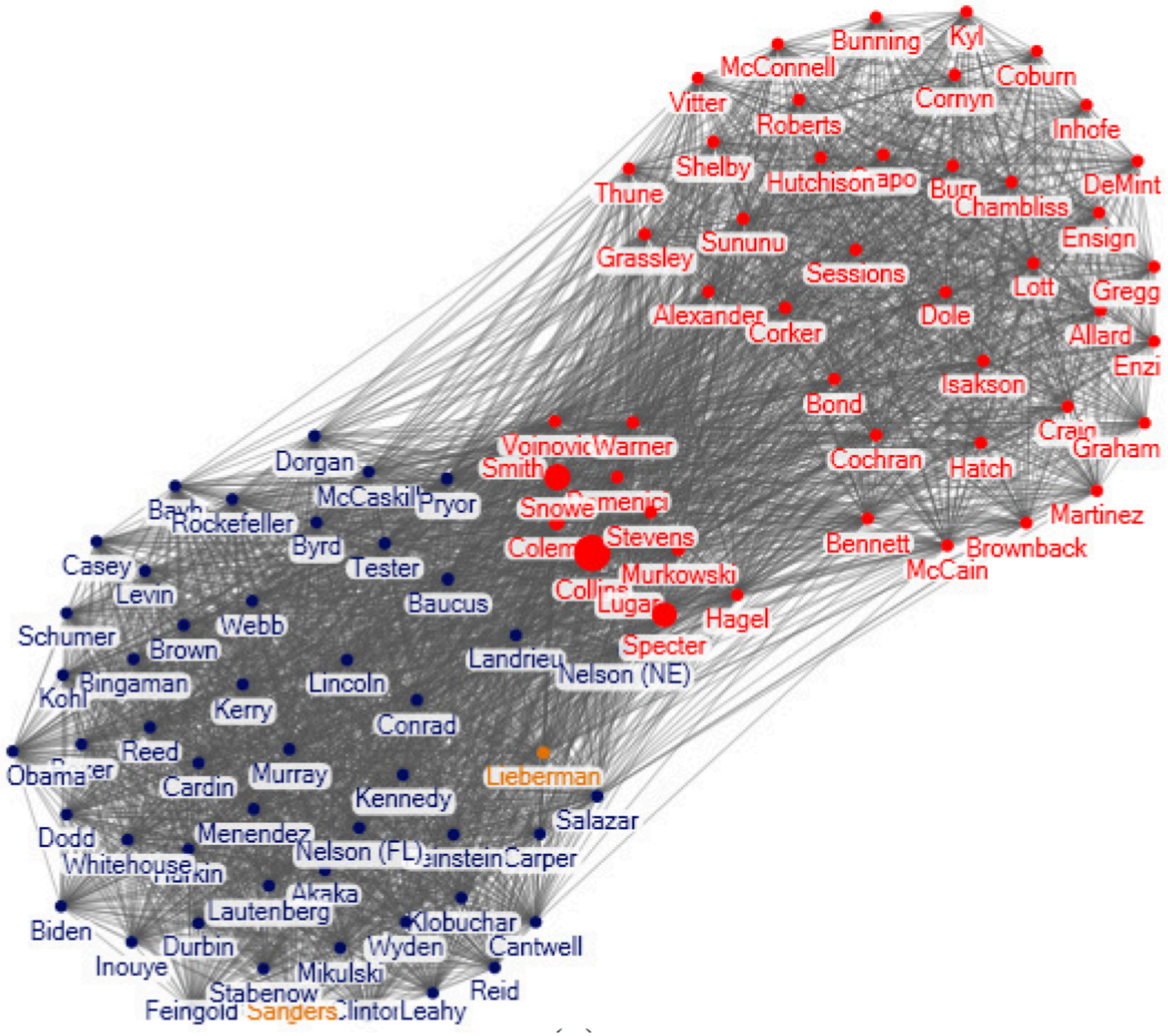


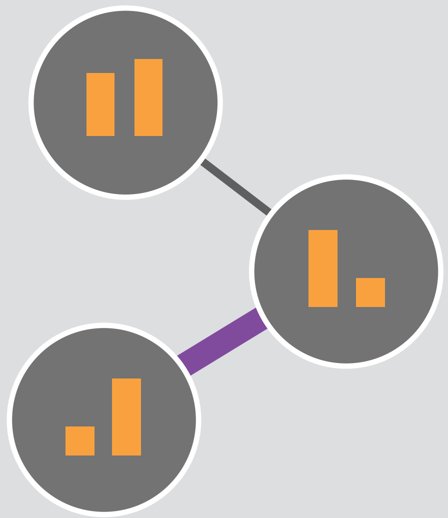
Attribute-Driven Faceting



On-Node / On-Edge Encoding

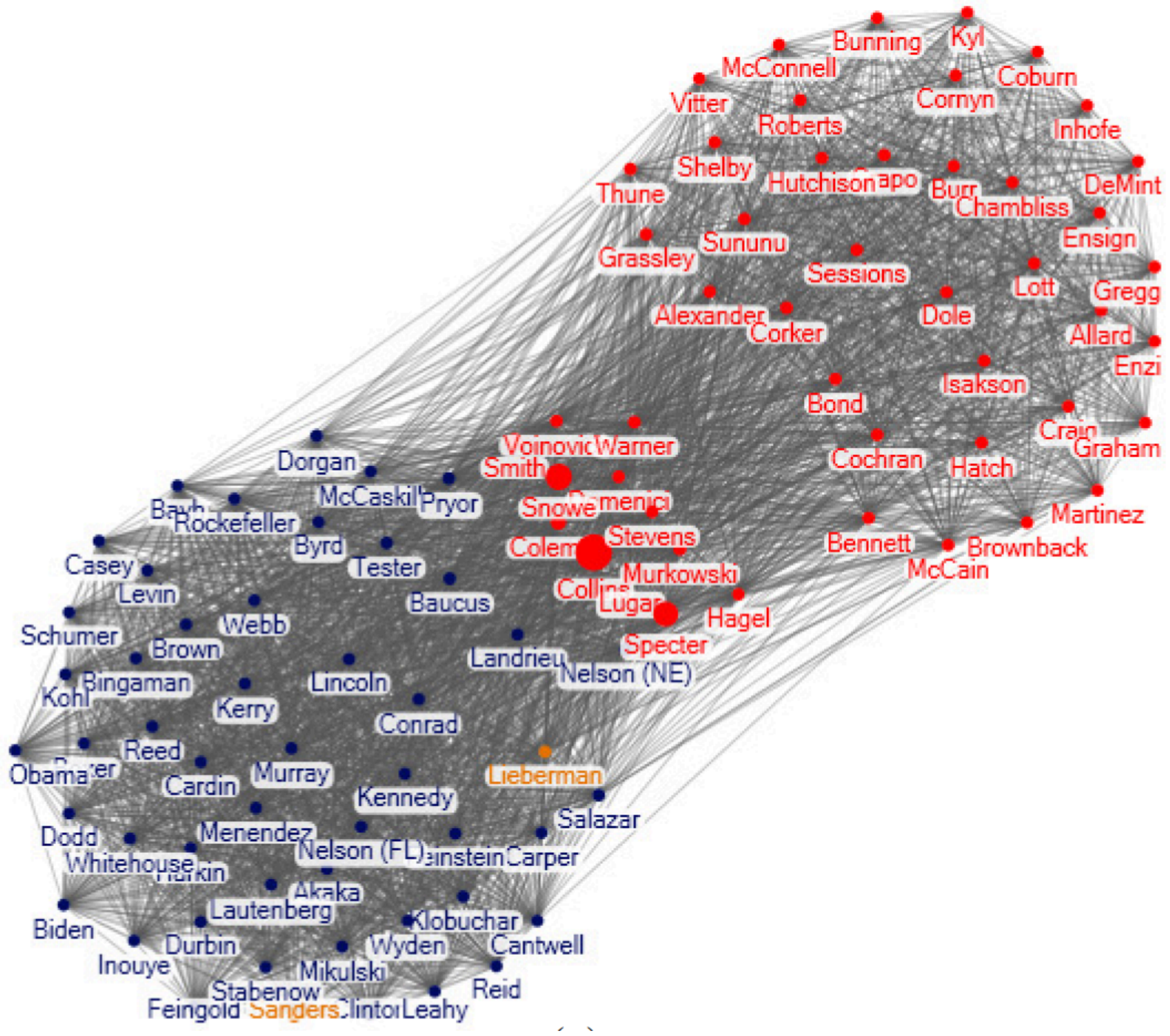
Group-in-a-box *Rodrigues et al. 2011*

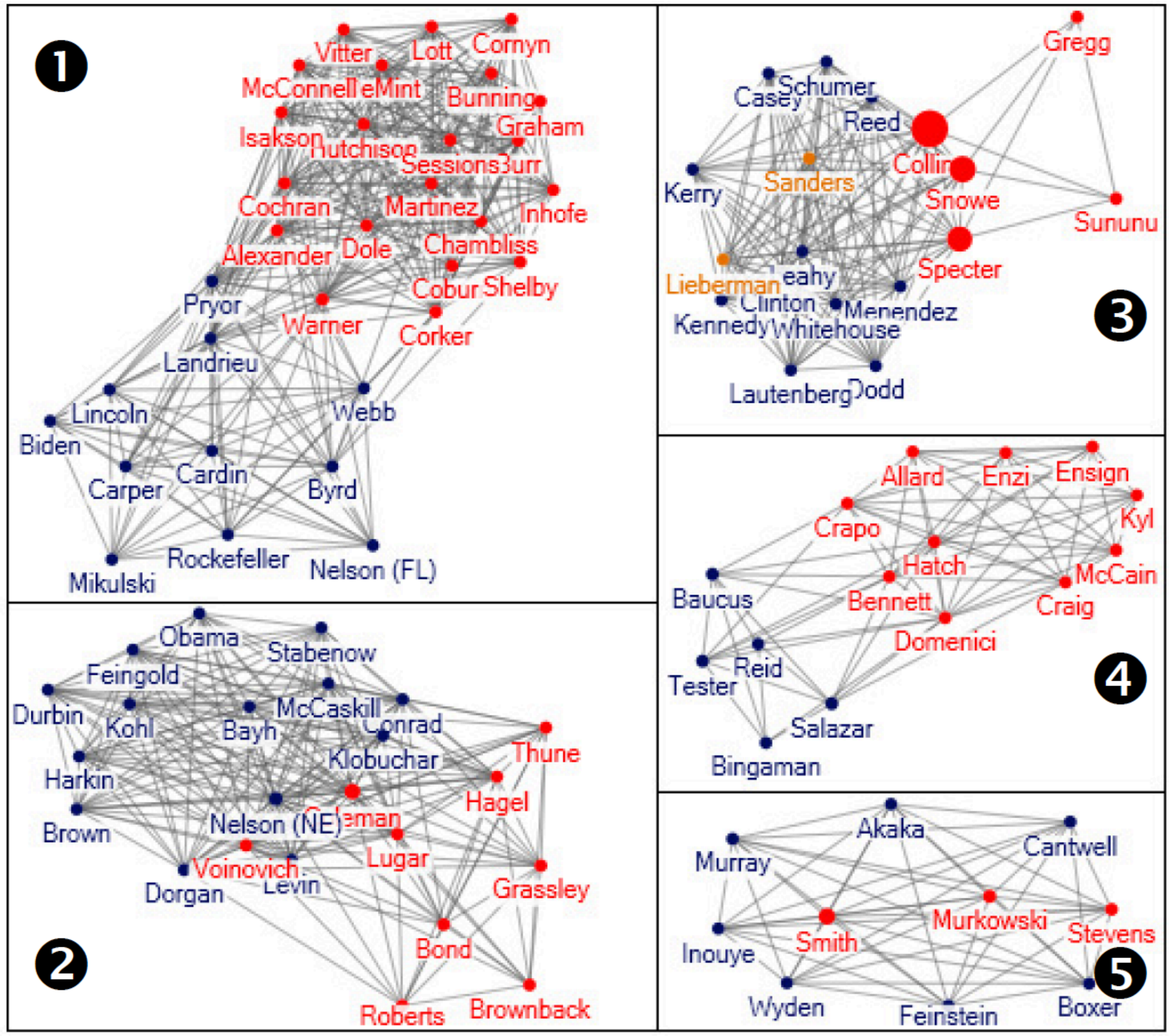


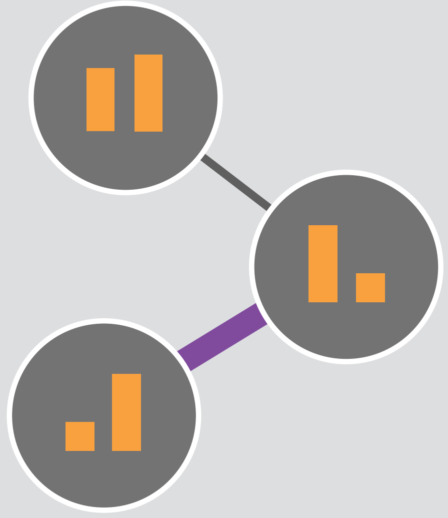


On-Node / On-Edge Encoding

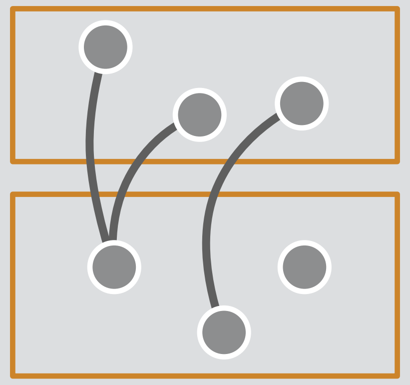
Group-in-a-box *Rodrigues et al. 2011*





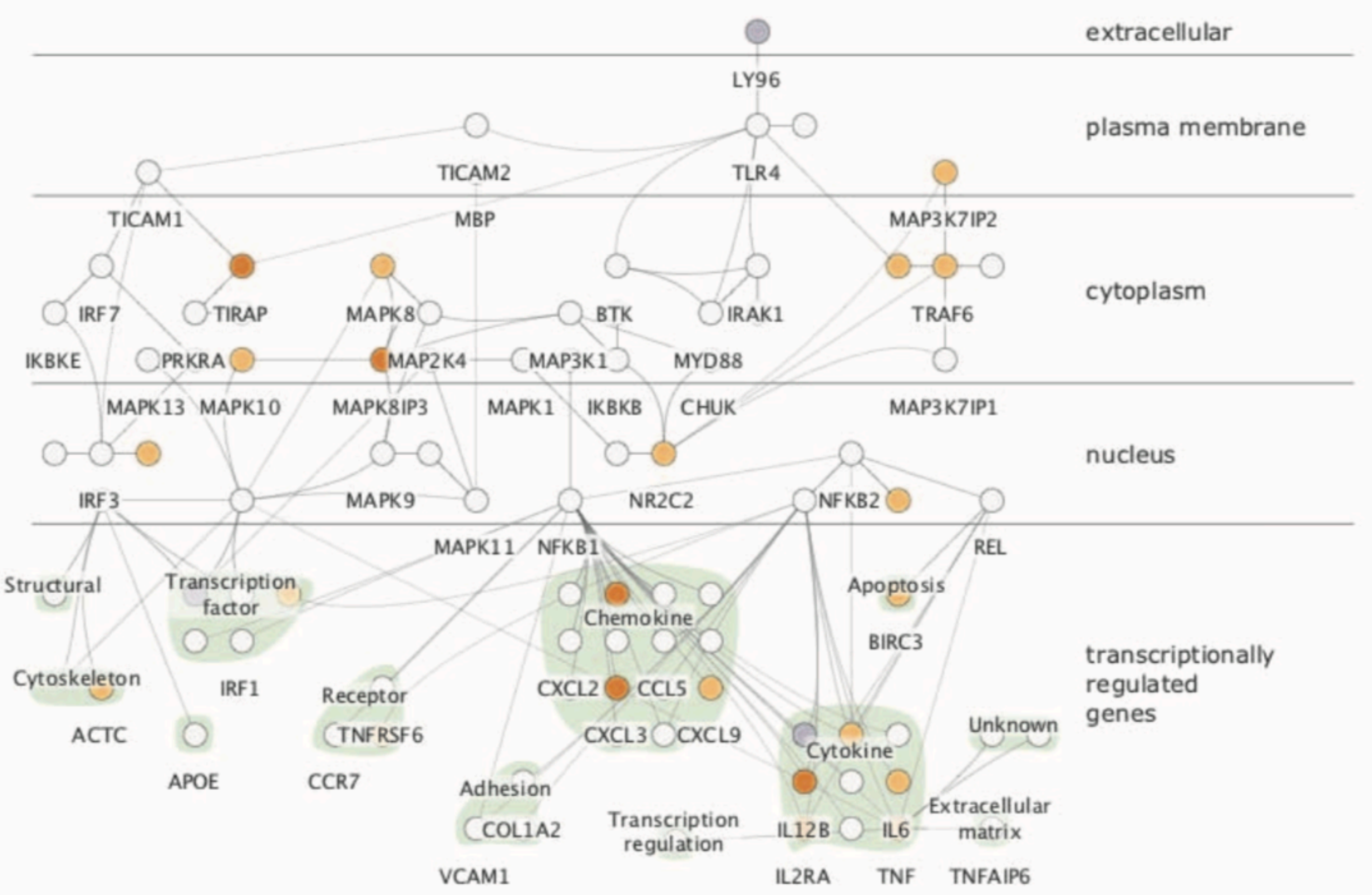


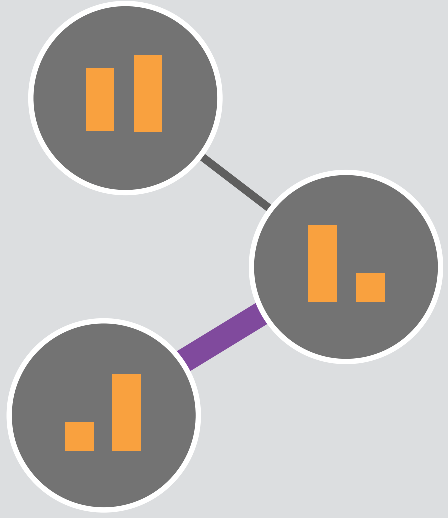
On-Node / On-Edge Encoding



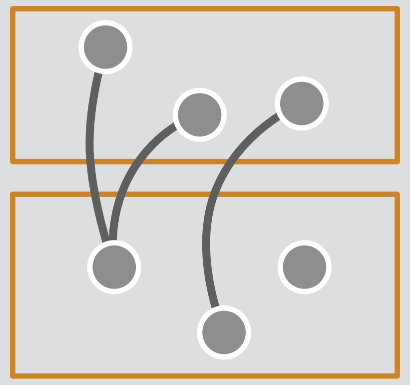
Attribute-Driven Faceting

Cerebral *Barskey et al. 2008*

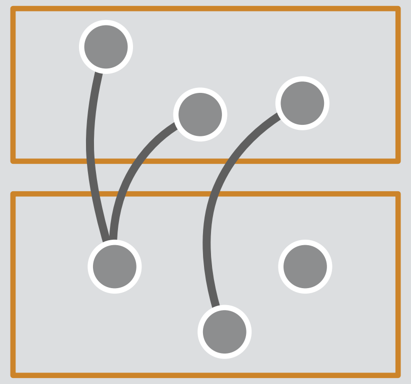




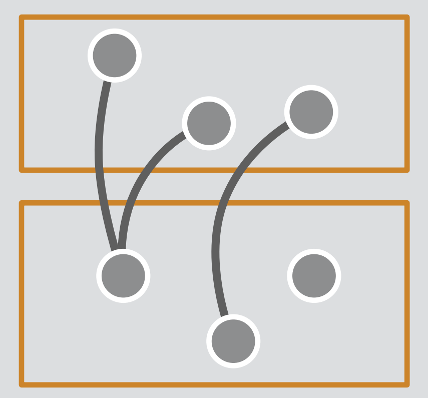
On-Node / On-Edge Encoding



Attribute-Driven Faceting



Attribute-Driven Faceting



Attribute-Driven Faceting

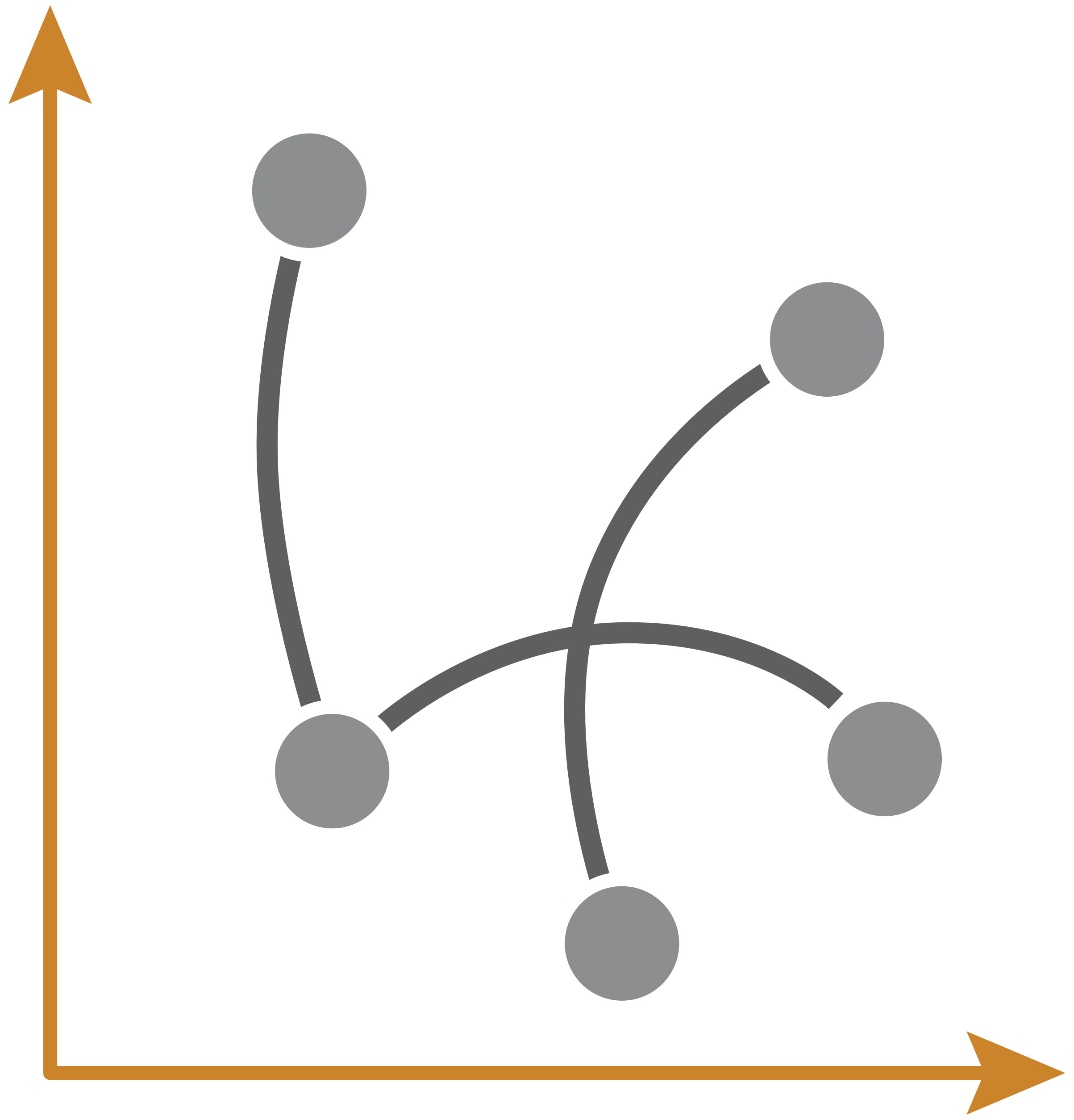
Well suited for networks with different node types or with an important categorical or set-like attribute.

Less scalable with respect to the number of nodes and network density than node-link layouts.

Neighborhoods, paths, and clusters are not easily visible if they span different facets.

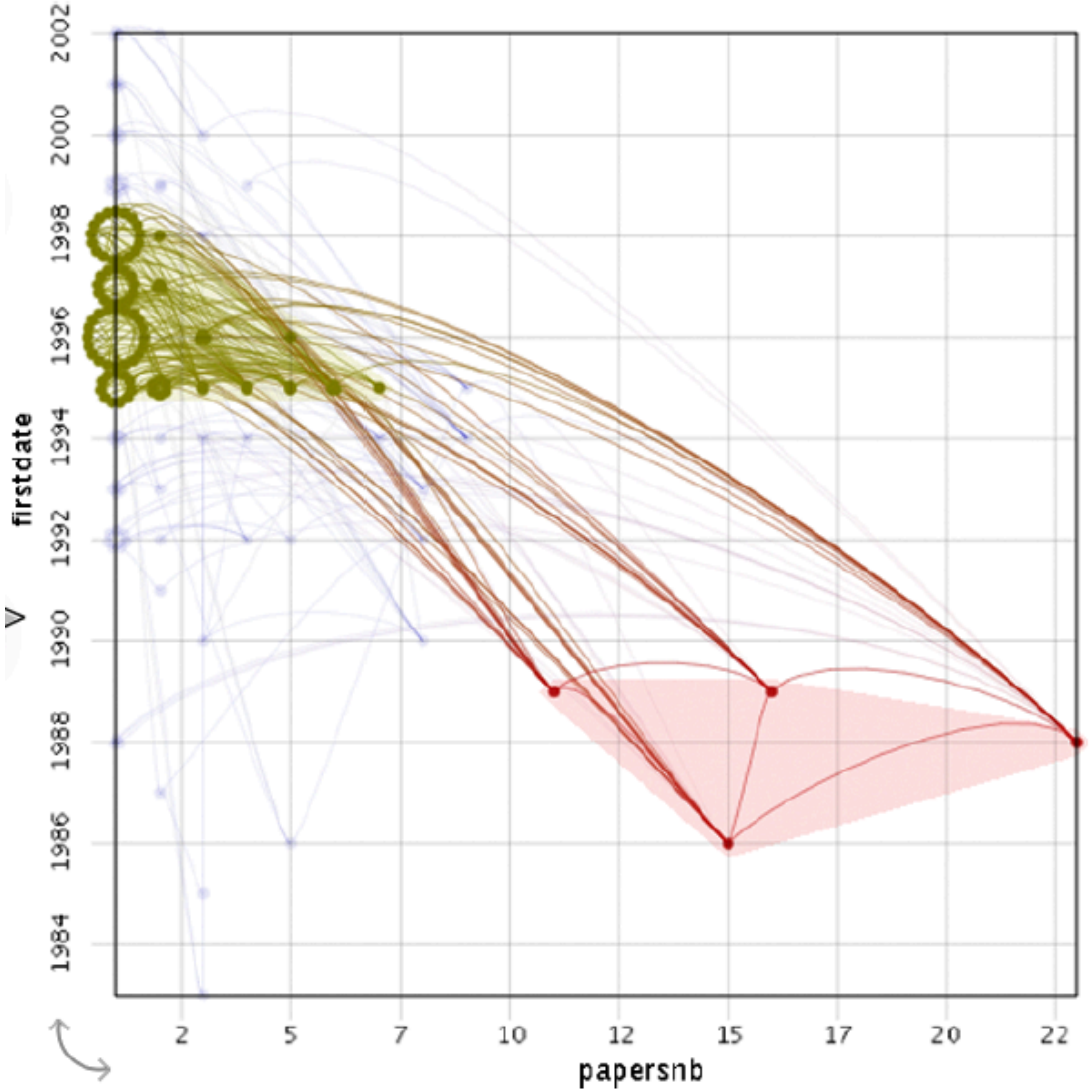
Recommended for networks where nodes can be separated into groups easily and where these groups are central to the analysis

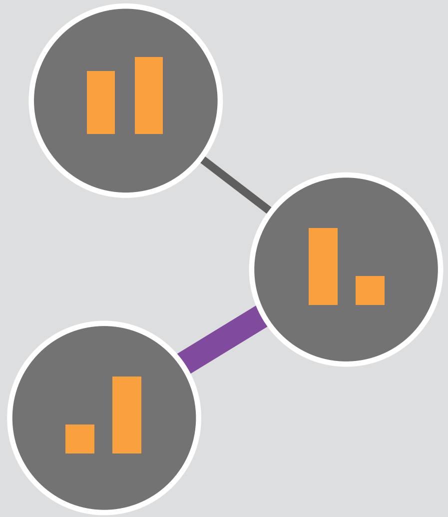
Attribute-Driven Positioning



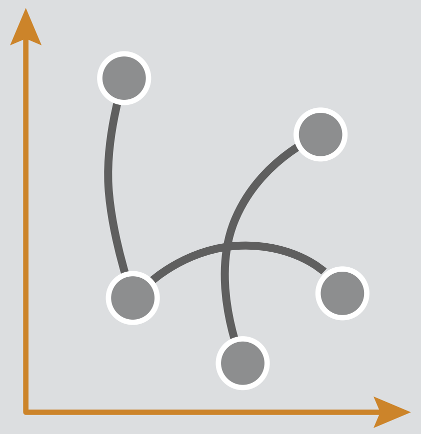

ANCHORAGE
VANCOUVER
EDMONTON
SEATTLE
PORTLAND
SAN FRANCISCO
DENVER
MINNEAPOLIS / ST. PAUL
CHICAGO
KANSAS CITY
DALLAS
TORONTO
CLEVELAND
MONTREAL
BALTIMORE
WASHINGTON D.C.
PHILADELPHIA
NEW YORK
JFK & NEWARK
BOSTON
HALIFAX
TAMPA BAY
ORLANDO
ICELAND
HELSINKI
STOCKHOLM
OSLO
GOTHENBURG
BERGEN
COPENHAGEN
BILLUND
BERLIN
HAMBURG
FRANKFURT
MUNICH
AMSTERDAM
GLASGOW
BRUSSELS
ZURICH
MANCHESTER
MILAN
LONDON
HEATHROW
& GATWICK
PARIS
ORLY & CDG
GENEVA
DUBLIN
MADRID

Graph Dice *Bezerianos et al. 2010*



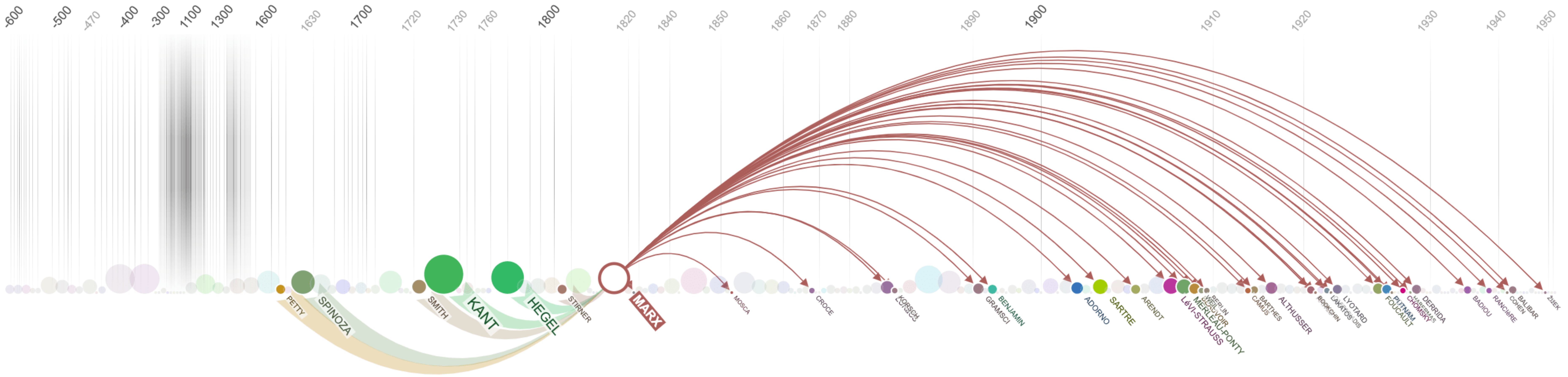


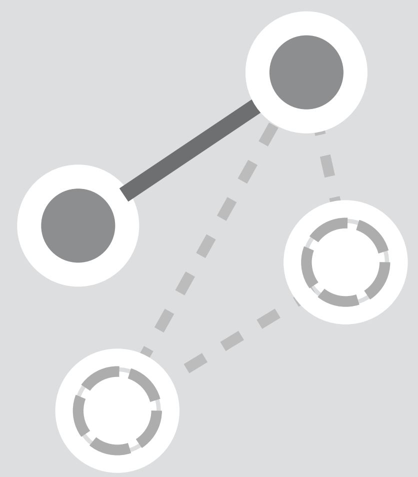
On-Node / On-Edge
Encoding



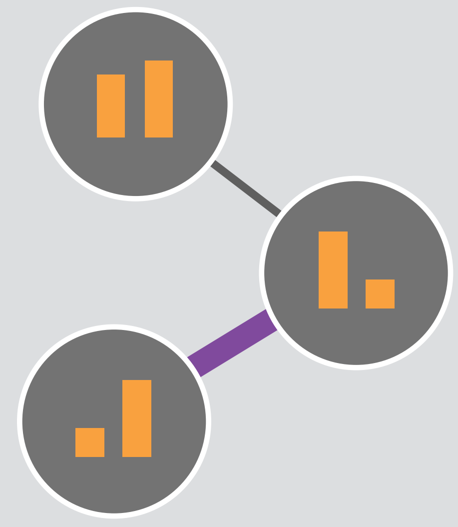
Attribute-Driven
Positioning

Edge Map *Dork et al. 2011*

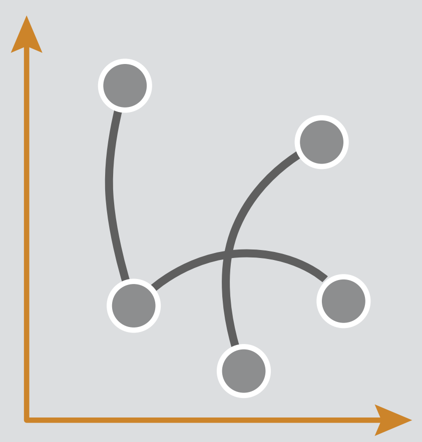




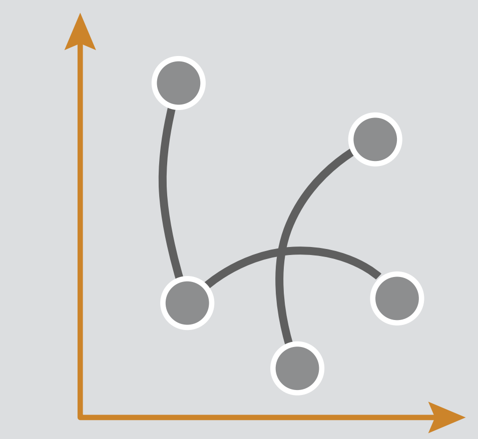
Querying and Filtering



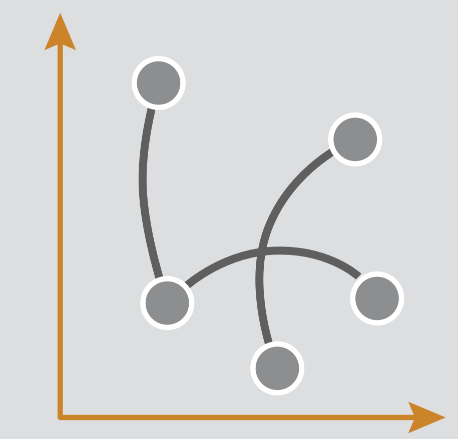
On-Node / On-Edge Encoding



Attribute-Driven Positioning



Attribute-Driven
Positioning



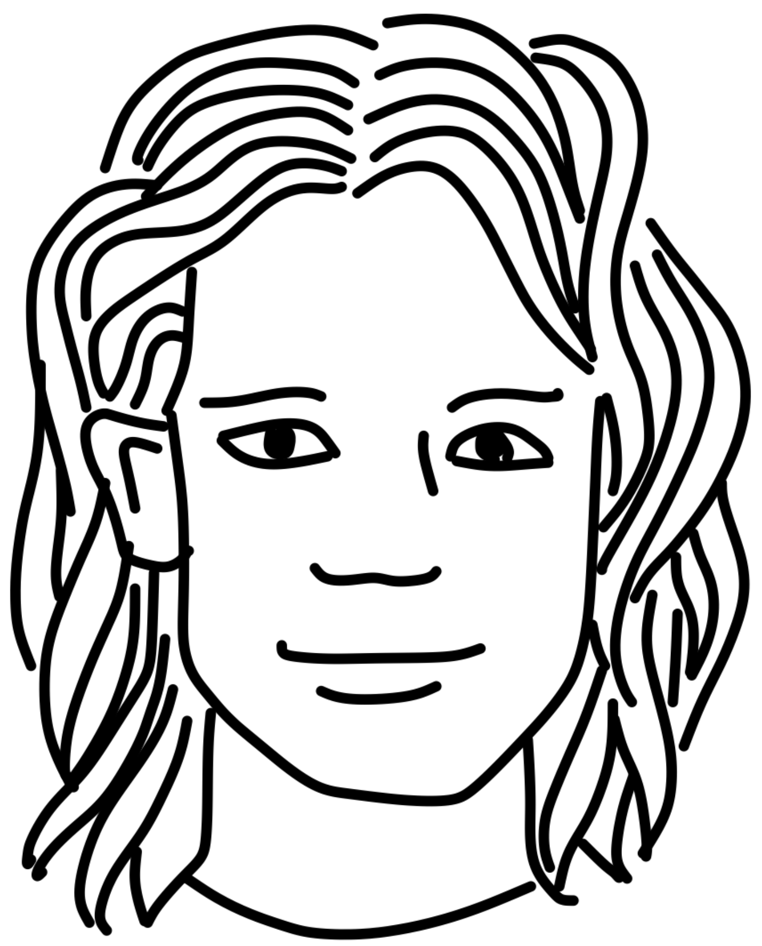
Attribute-Driven Positioning

Well suited for quantitative attributes

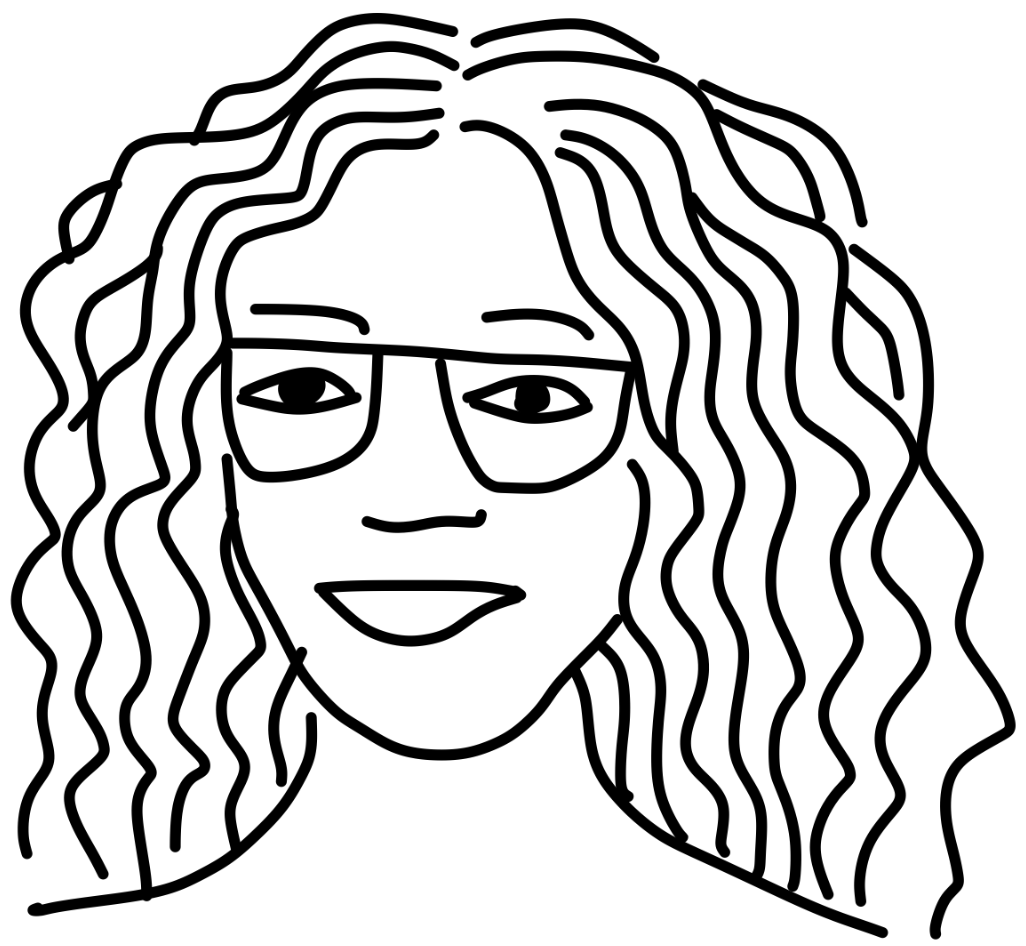
Does not lend itself well to visualizing the topology of the network.

Recommended for smaller, sparse networks where relationships between node attributes are paramount to the analysis task, and topological features only provide context

Tools and Applications

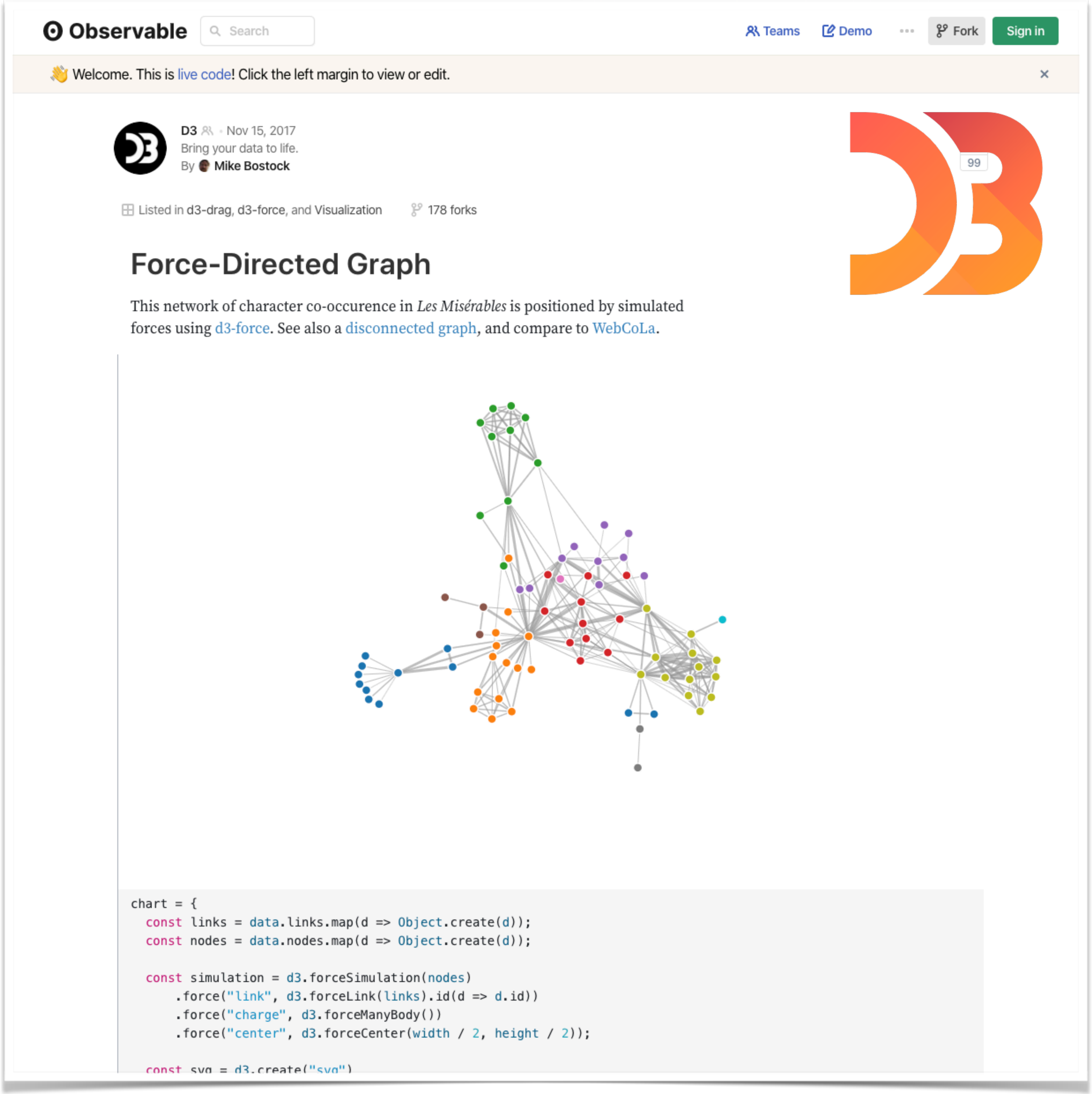


Brad
graphic designer



Maya
developer


developer


Observable
Search
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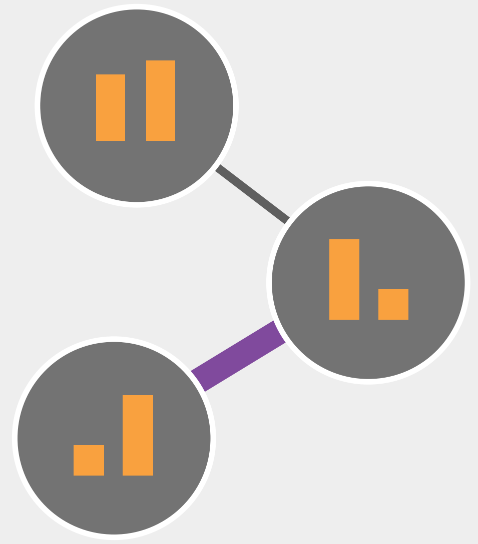
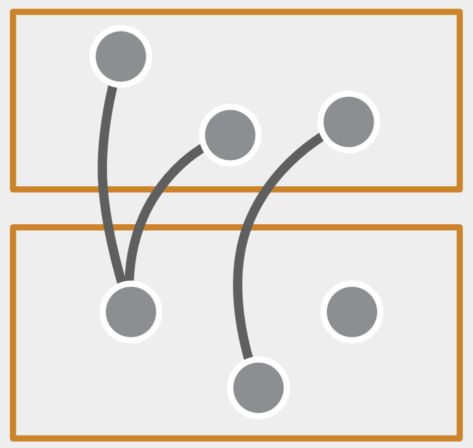
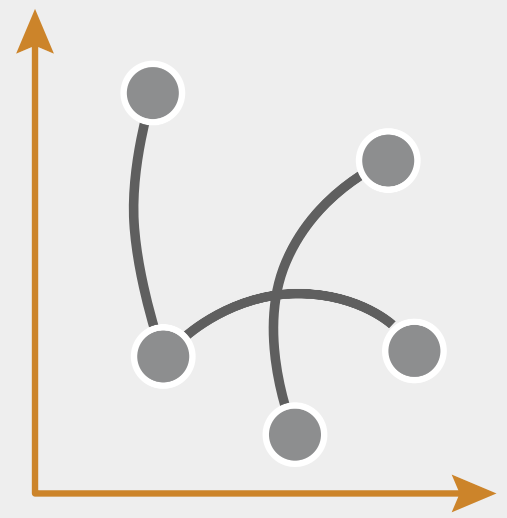
Welcome. This is live code! Click the left margin to view or edit.
D3 · Nov 15, 2017
Bring your data to life.
By Mike Bostock
Listed in d3-drag, d3-force, and Visualization
178 forks
99
Force-Directed Graph
This network of character co-occurence in Les Misérables is positioned by simulated forces using d3-force. See also a disconnected graph, and compare to WebCoLa.
chart = {
const links = data.links.map(d => Object.create(d));
const nodes = data.nodes.map(d => Object.create(d));
const simulation = d3.forceSimulation(nodes)
.force("link", d3.forceLink(links).id(d => d.id))
.force("charge", d3.forceManyBody())
.force("center", d3.forceCenter(width / 2, height / 2));
const svg = d3.create("svg")





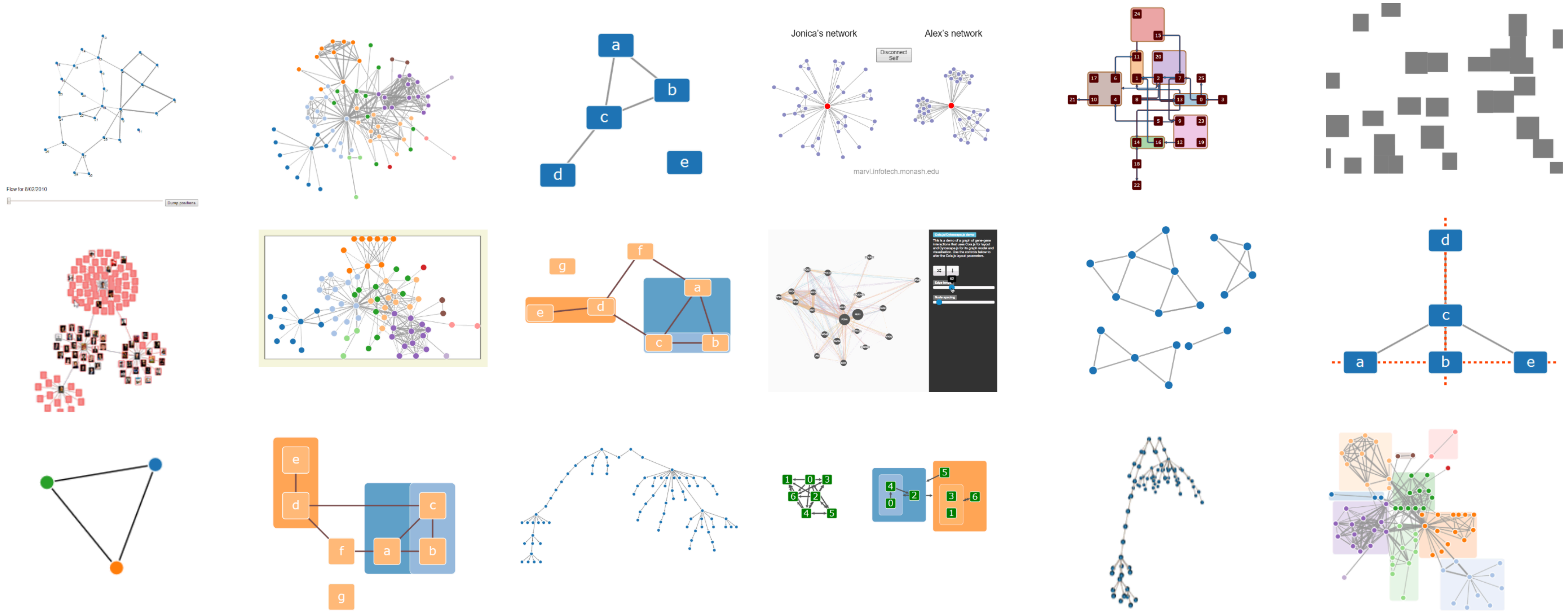


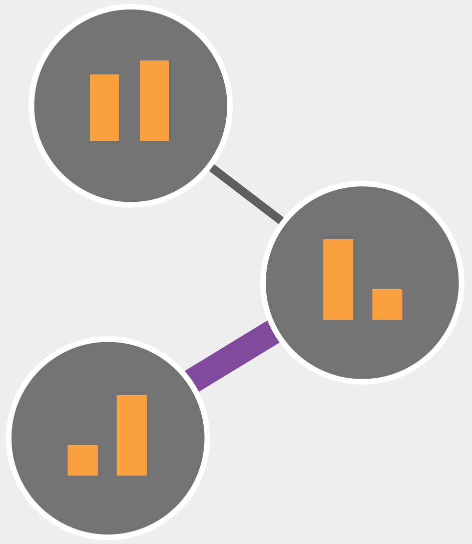
Cola.js (A.K.A. "WebCoLa") is an open-source JavaScript library for arranging your HTML5 documents and diagrams using constraint-based optimization techniques.

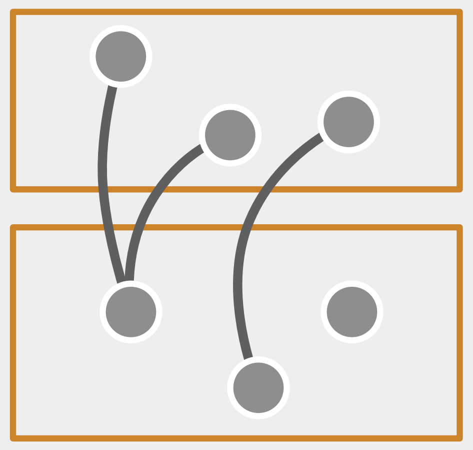
Overview Wiki API Source

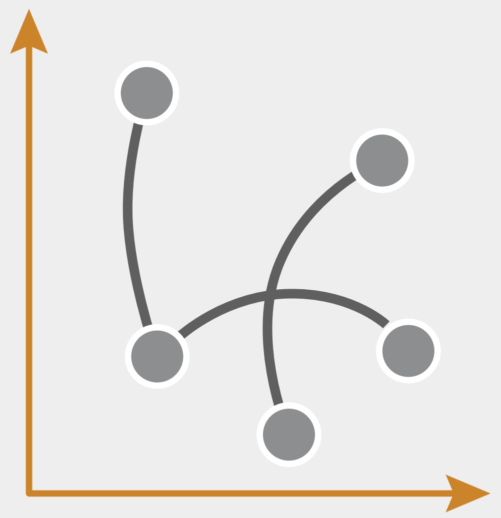
cola.js

Constraint-Based Layout in the Browser







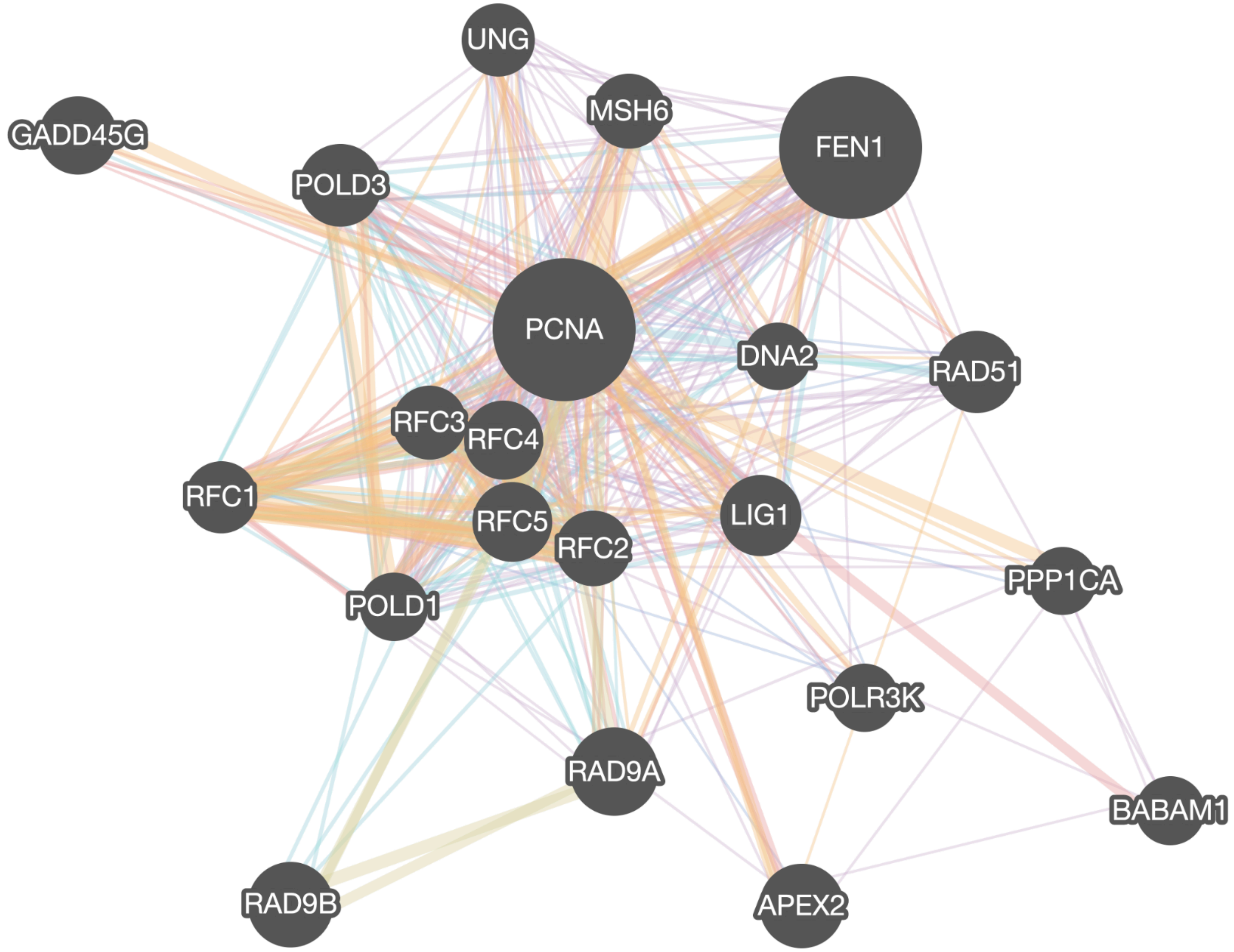


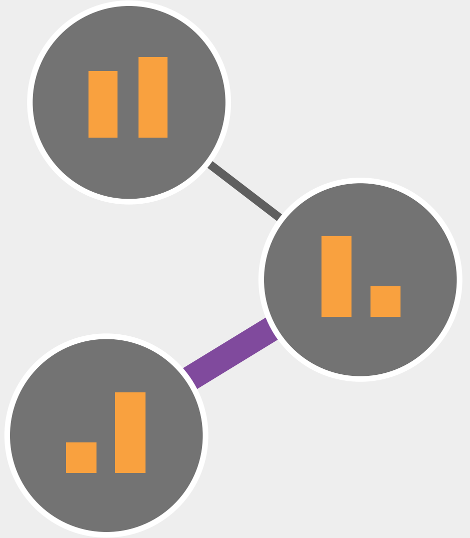
Cytoscape.js

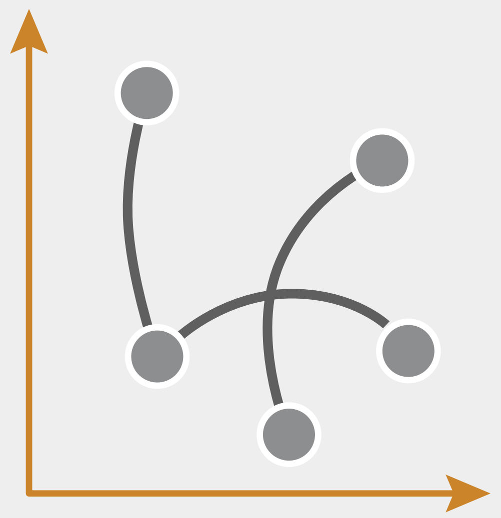
Graph theory (network) library for visualisation and analysis

Repo GitHub | Updates Twitter | News and tutorials Blog | Questions StackOverflow | Ask a question StackOverflow

npm installs 100k/month | master branch passing | unstable branch passing | Greenkeeper enabled







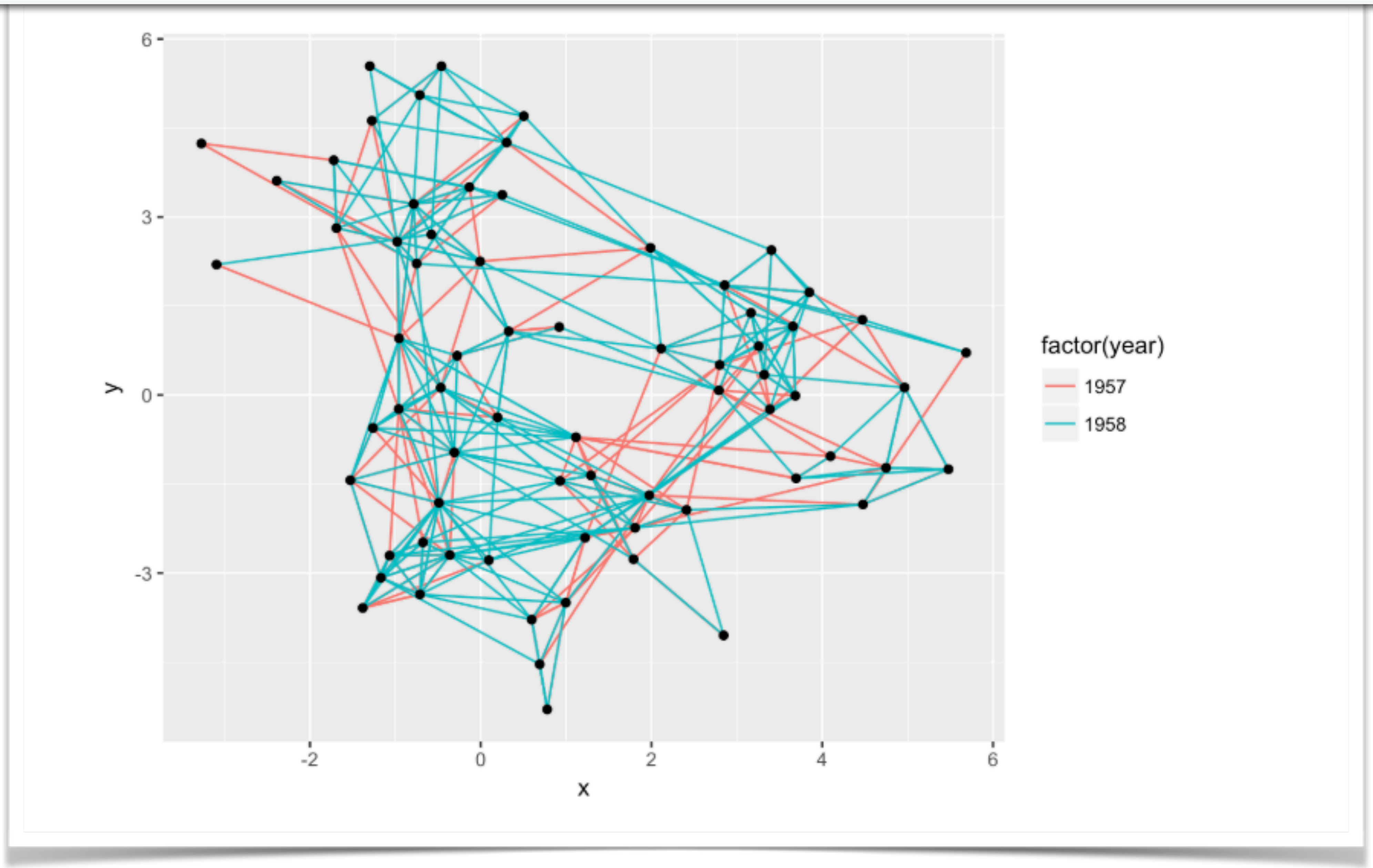
GGRAPH 1.0.2.9999 Reference Getting Started Articles News

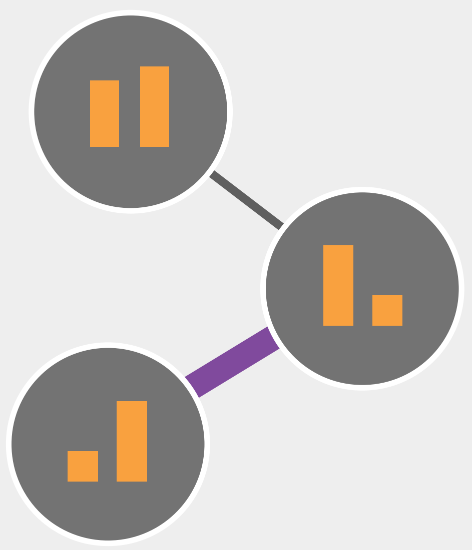
ggraph

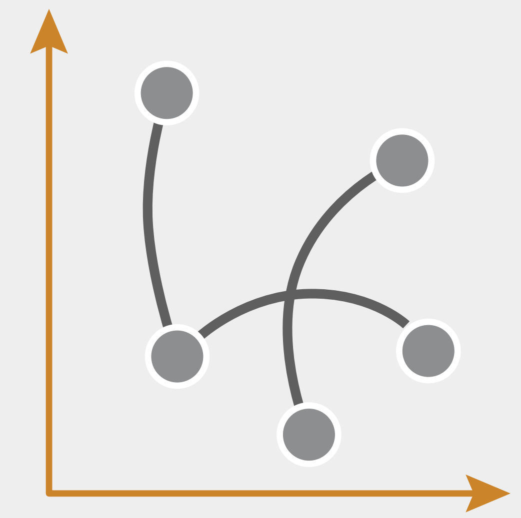
/dʒiː.dʒɪˈrɑːf/ (or g-giraffe)

A grammar of graphics for relational data

ggraph is an extension of `ggplot2` aimed at supporting relational data structures such as networks, graphs, and trees. While it builds upon the foundation of `ggplot2` and its API it comes with its own self-contained set of geoms, facets, etc., as well as adding the concept of *layouts* to the grammar.

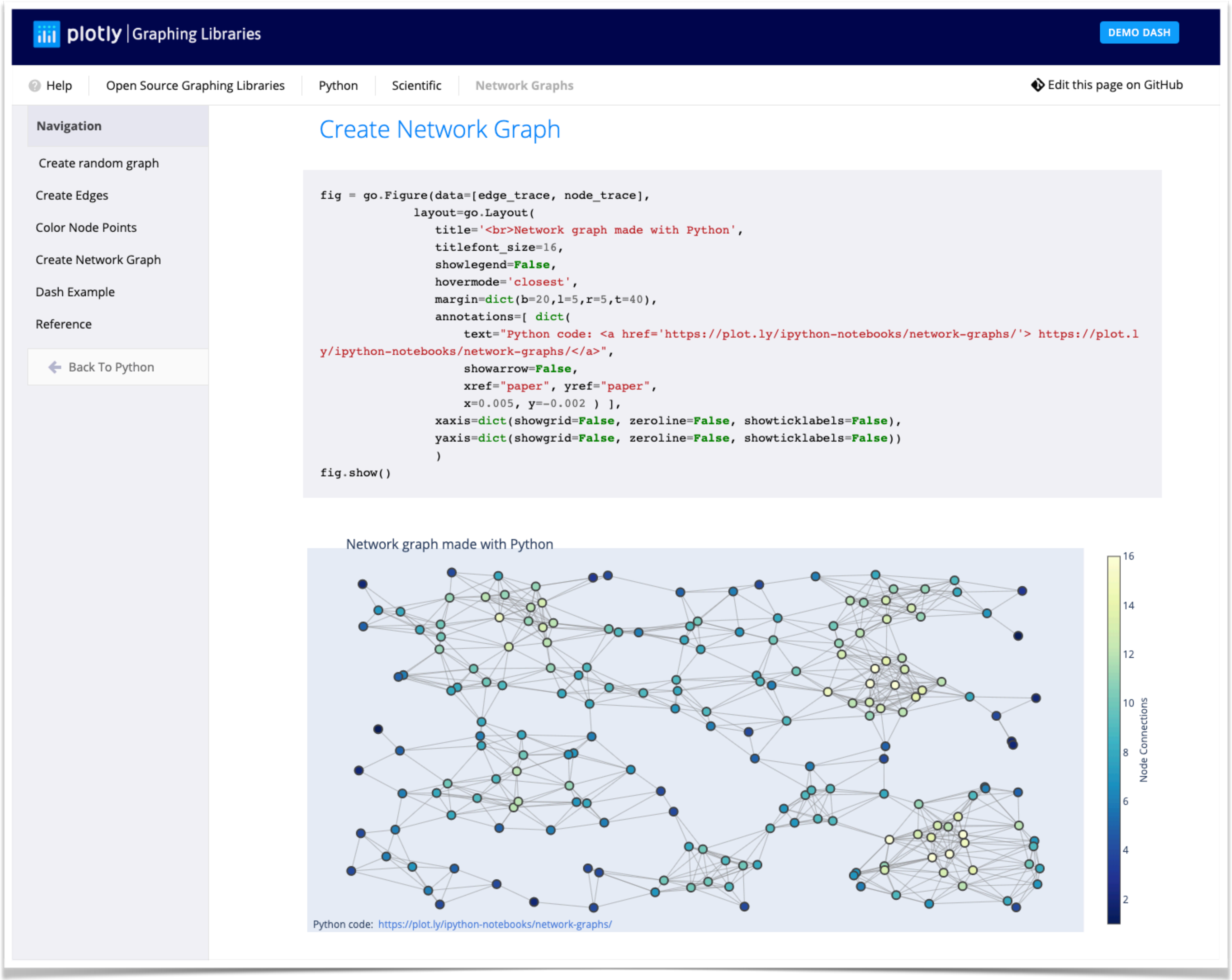


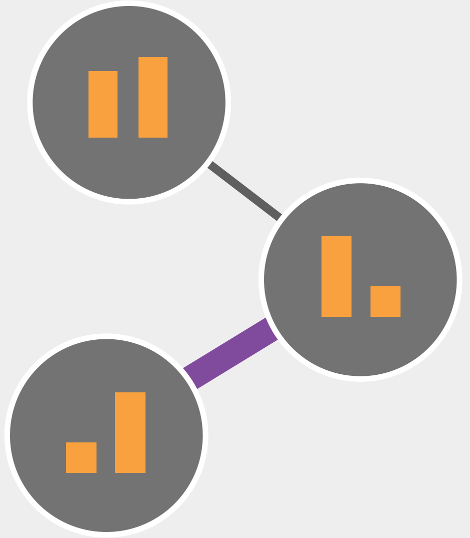


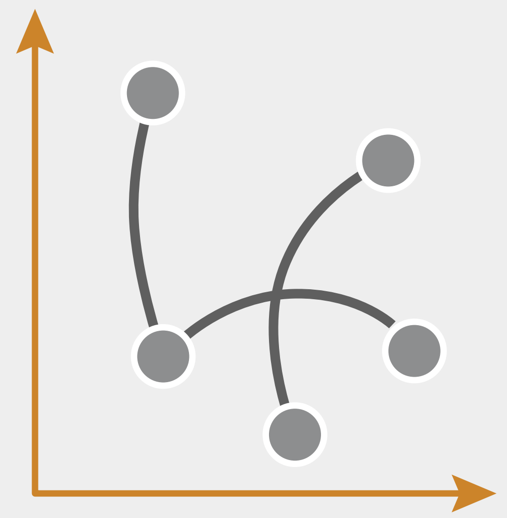



developer

python


plotly | Graphing Libraries
DEMO DASH
Help
Open Source Graphing Libraries
Python
Scientific
Network Graphs
Edit this page on GitHub
Navigation
Create random graph
Create Edges
Color Node Points
Create Network Graph
Dash Example
Reference
Back To Python
Create Network Graph
fig = go.Figure(data=[edge_trace, node_trace],
layout=go.Layout(
title='
Network graph made with Python',
titlefont_size=16,
showlegend=False,
hovermode='closest',
margin=dict(b=20,l=5,r=5,t=40),
annotations=[dict(
text="Python code: https://plot.ly/ipython-notebooks/network-graphs/",
showarrow=False,
xref="paper", yref="paper",
x=0.005, y=-0.002)],
xaxis=dict(showgrid=False, zeroline=False, showticklabels=False),
yaxis=dict(showgrid=False, zeroline=False, showticklabels=False))
)
fig.show()
Network graph made with Python
Node Connections
16
14
12
10
8
6
4
2
Python code: https://plot.ly/ipython-notebooks/network-graphs/





NetworkX

Stable (notes)

2.3 — April 2019
download | doc | pdf

Latest (notes)

2.4 development
github | doc | pdf

Archive

Contact

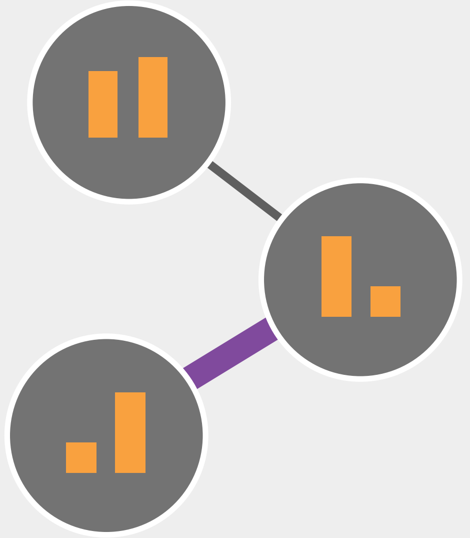
Mailing list
Issue tracker

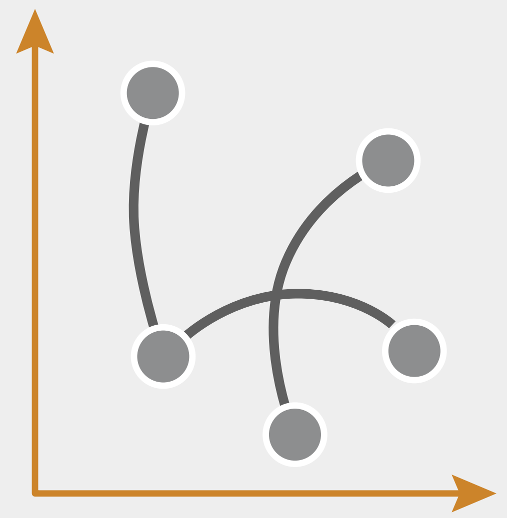
Software for complex networks

NetworkX is a Python package for the creation, manipulation, and study of the structure, dynamics, and functions of complex networks.

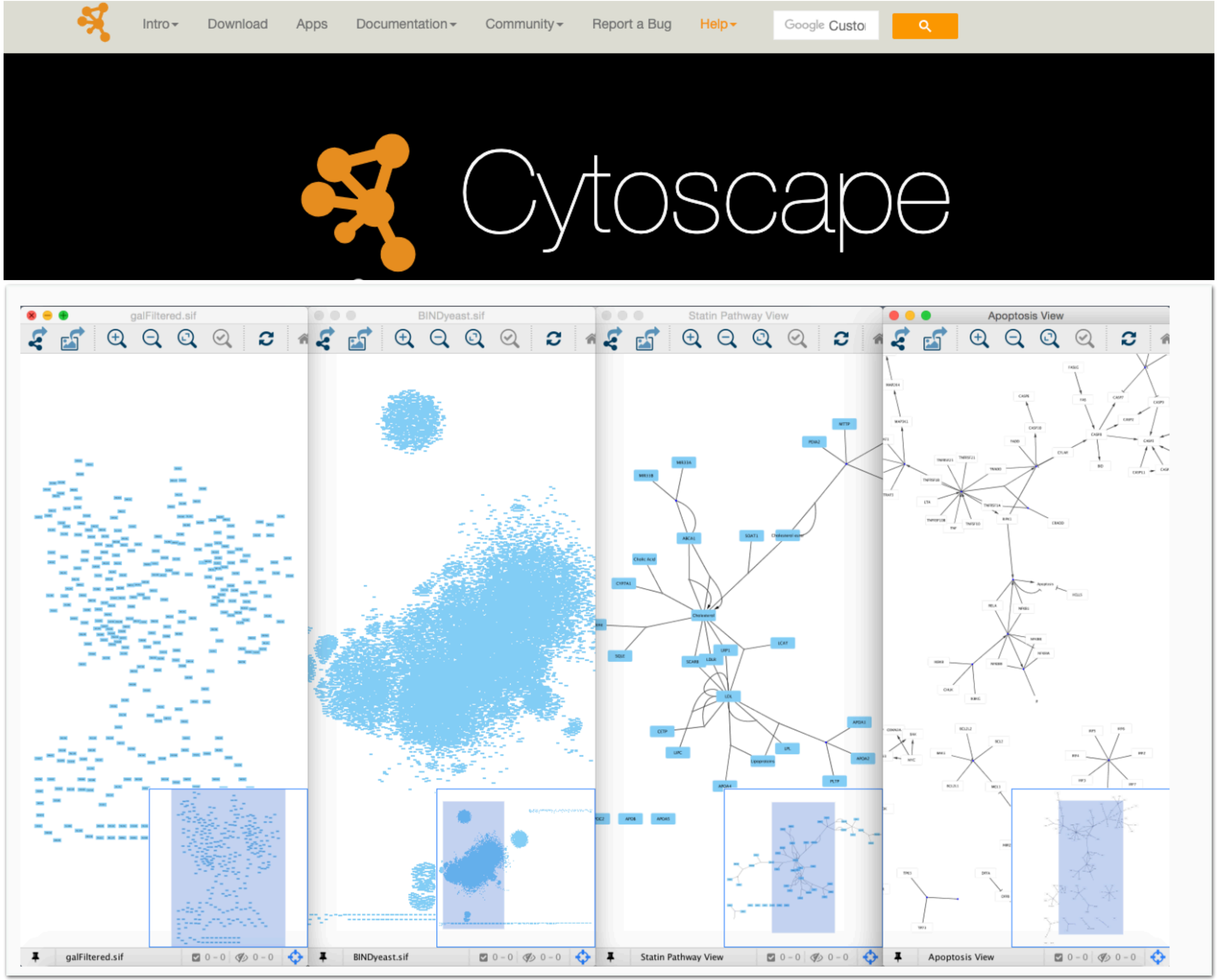
Features

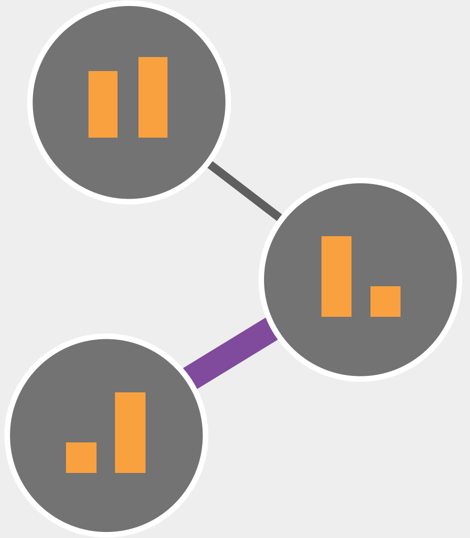
- Data structures for graphs, digraphs, and multigraphs
- Many standard graph algorithms
- Network structure and analysis measures
- Generators for classic graphs, random graphs, and synthetic networks
- Nodes can be "anything" (e.g., text, images, XML records)
- Edges can hold arbitrary data (e.g., weights, time-series)
- Open source 3-clause BSD license
- Well tested with over 90% code coverage
- Additional benefits from Python include fast prototyping, easy to teach, and multi-platform

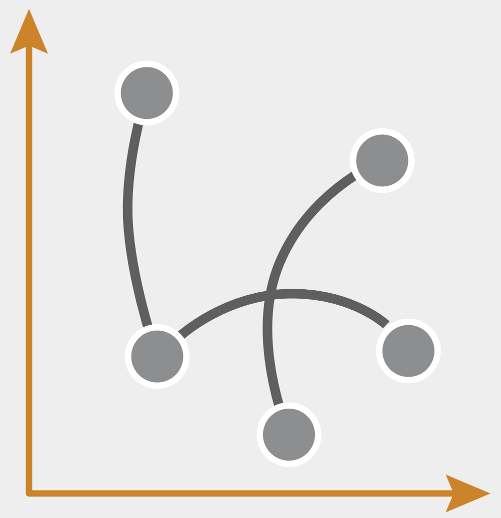




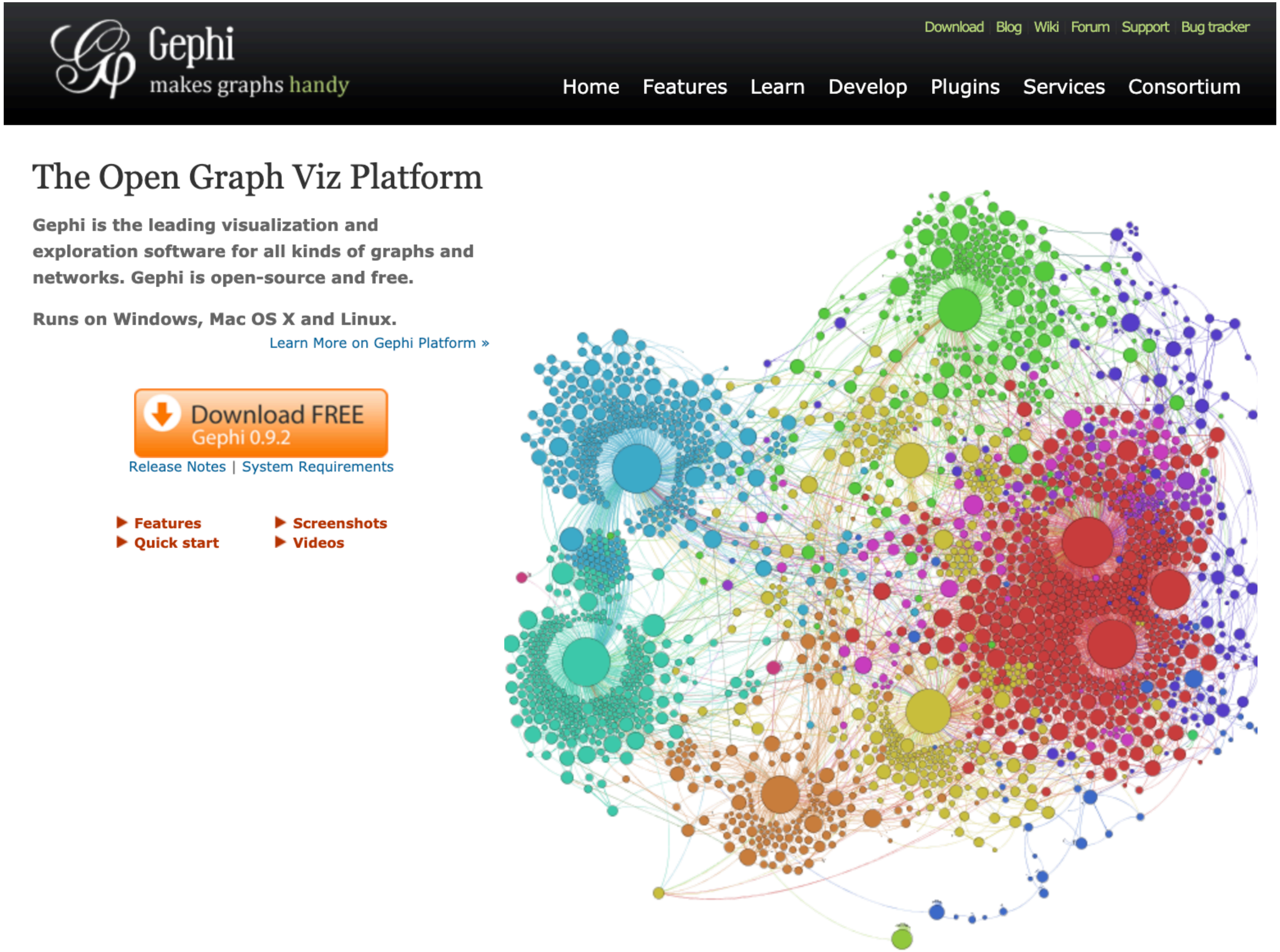
graphic designer

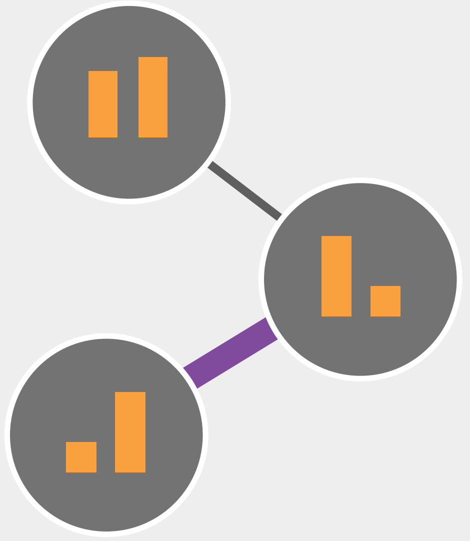


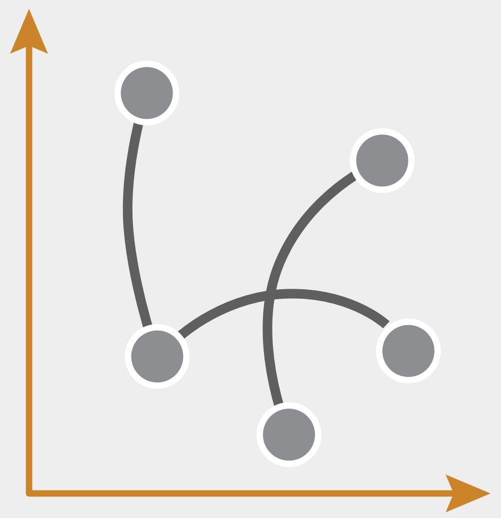




graphic designer

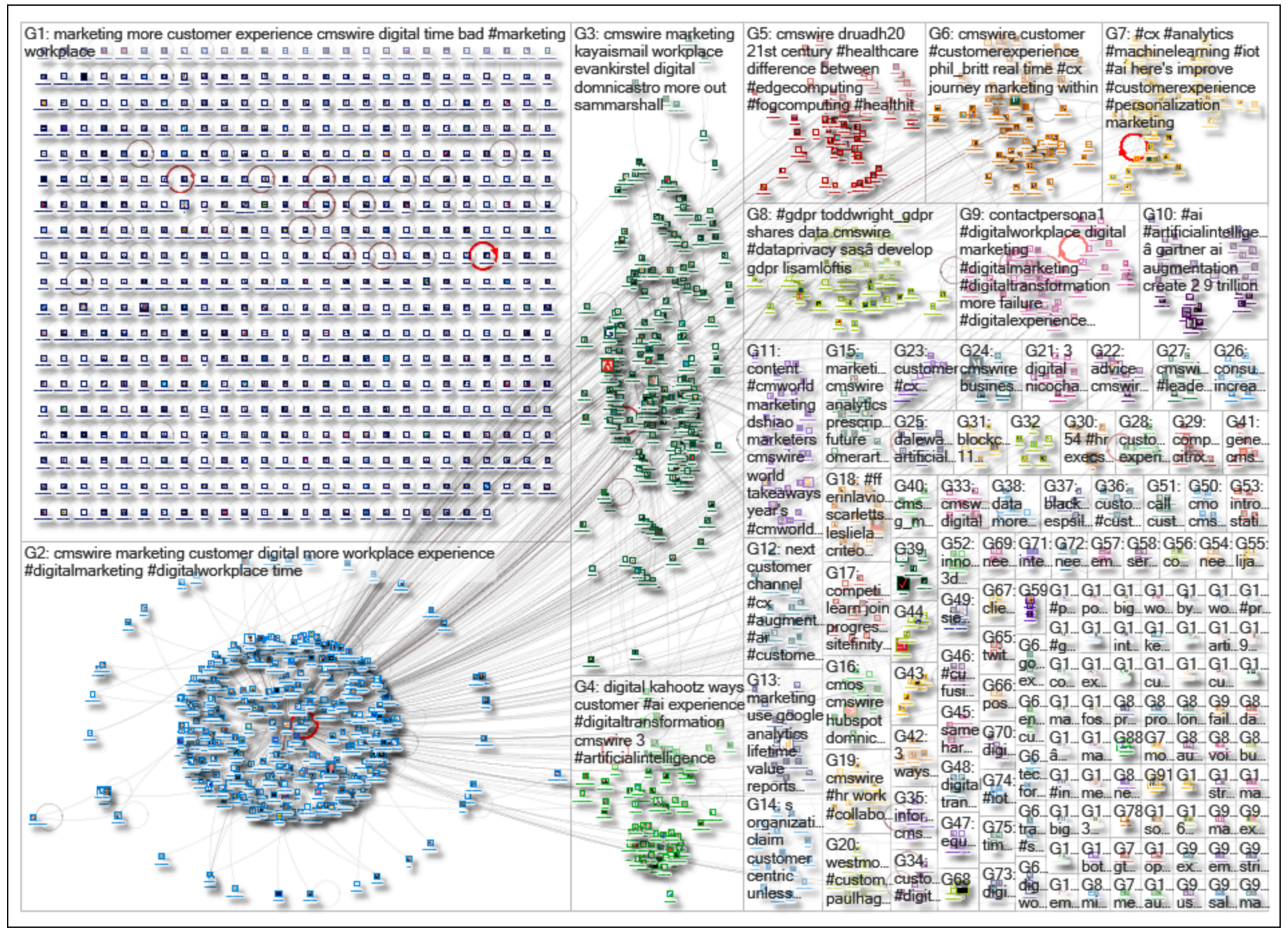


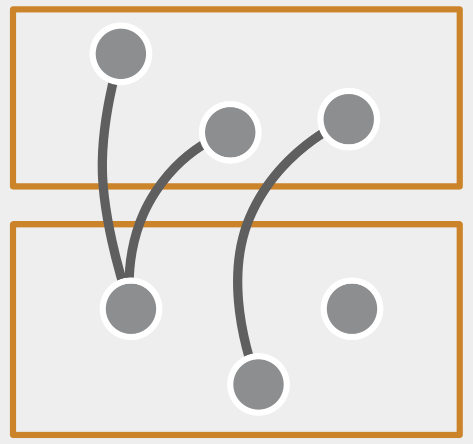




graphic designer

NODE

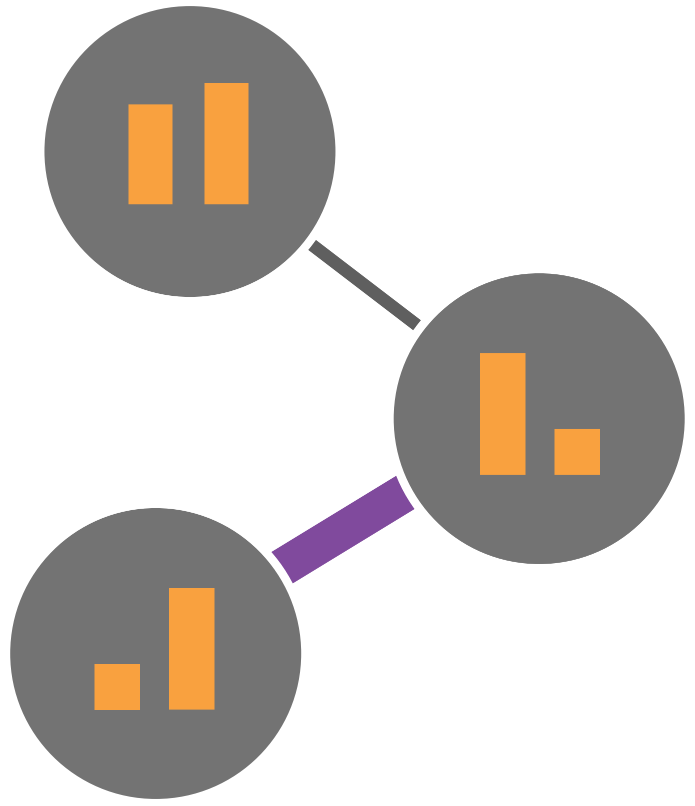




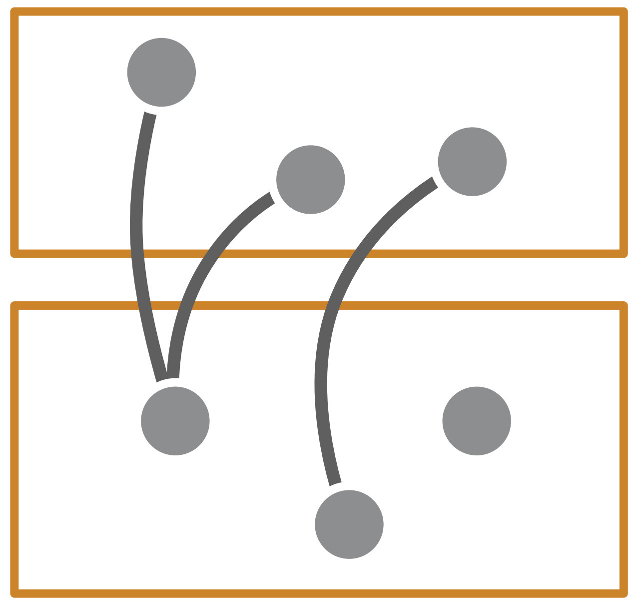
Node-Link Activity

Form groups of 3–5 people

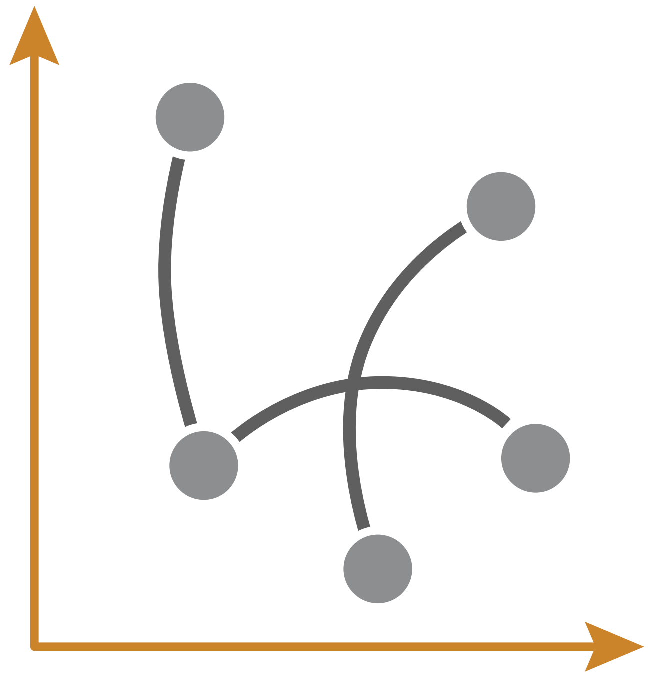
Choose 1 node-link technique per group



On-Node / On-Edge
Encoding



Attribute-Driven
Faceting

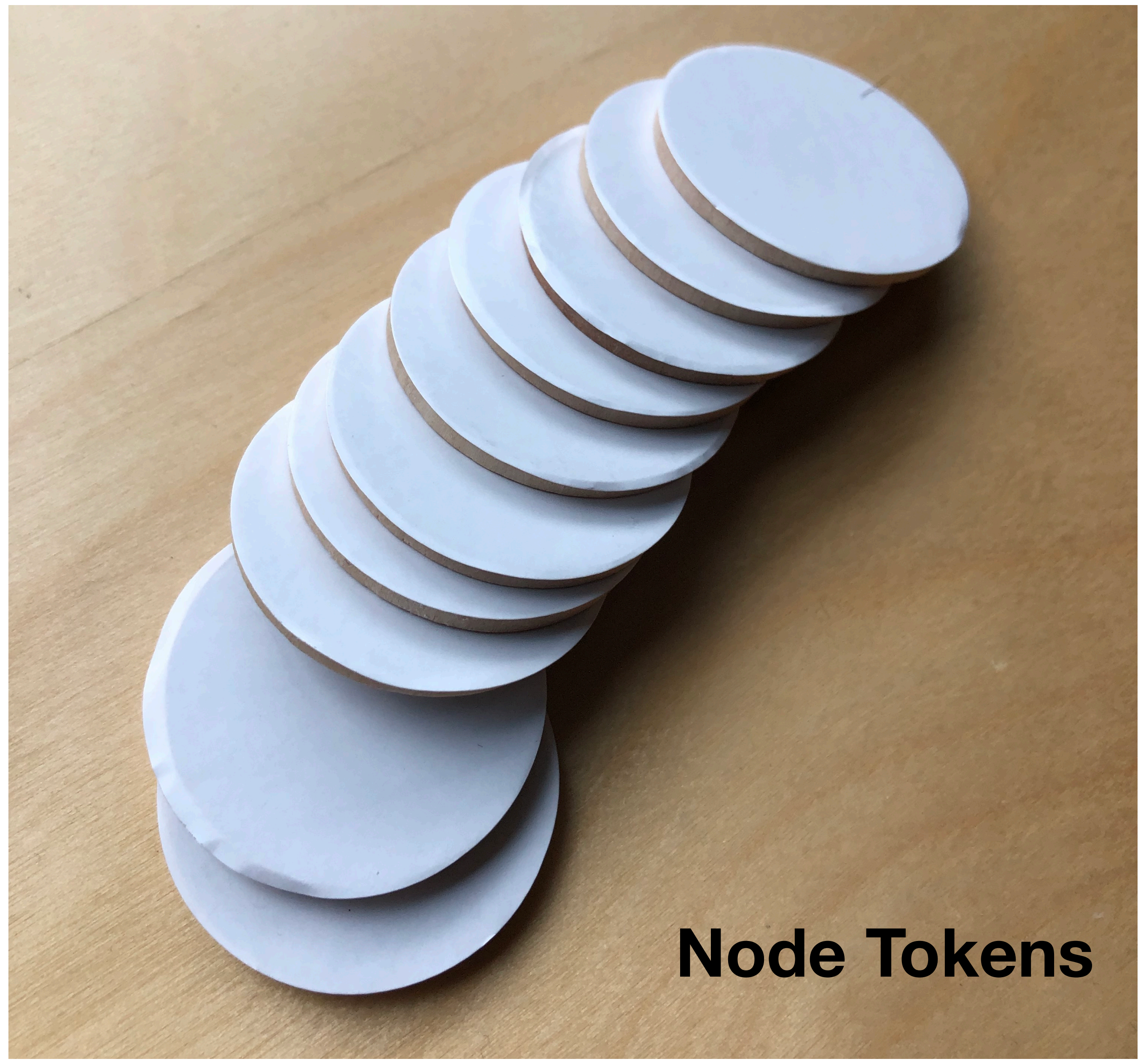


Attribute-Driven
Positioning

Nodes

	Name	#Tweets	Following	Account Type
1	Michelle Obama	1,178	18	Person
2	Tina Tchen	428	173	Person
3	Time's Up	3,092	634	Organization
4	NowThis	*13,530*	*1,216*	Organization
5	Kerry Washington	*3,011*	676	Person
6	MeToo	330	337	Organization
7	Monica Ramirez	7,839	1,248	Person
8	National Women's Law Center	*3,722*	2,698	Organization
9	Justice 4 Migrant Women	1,174	143	Organization
10	Alexandria Ocasio-Cortez	9,182	1,729	Person

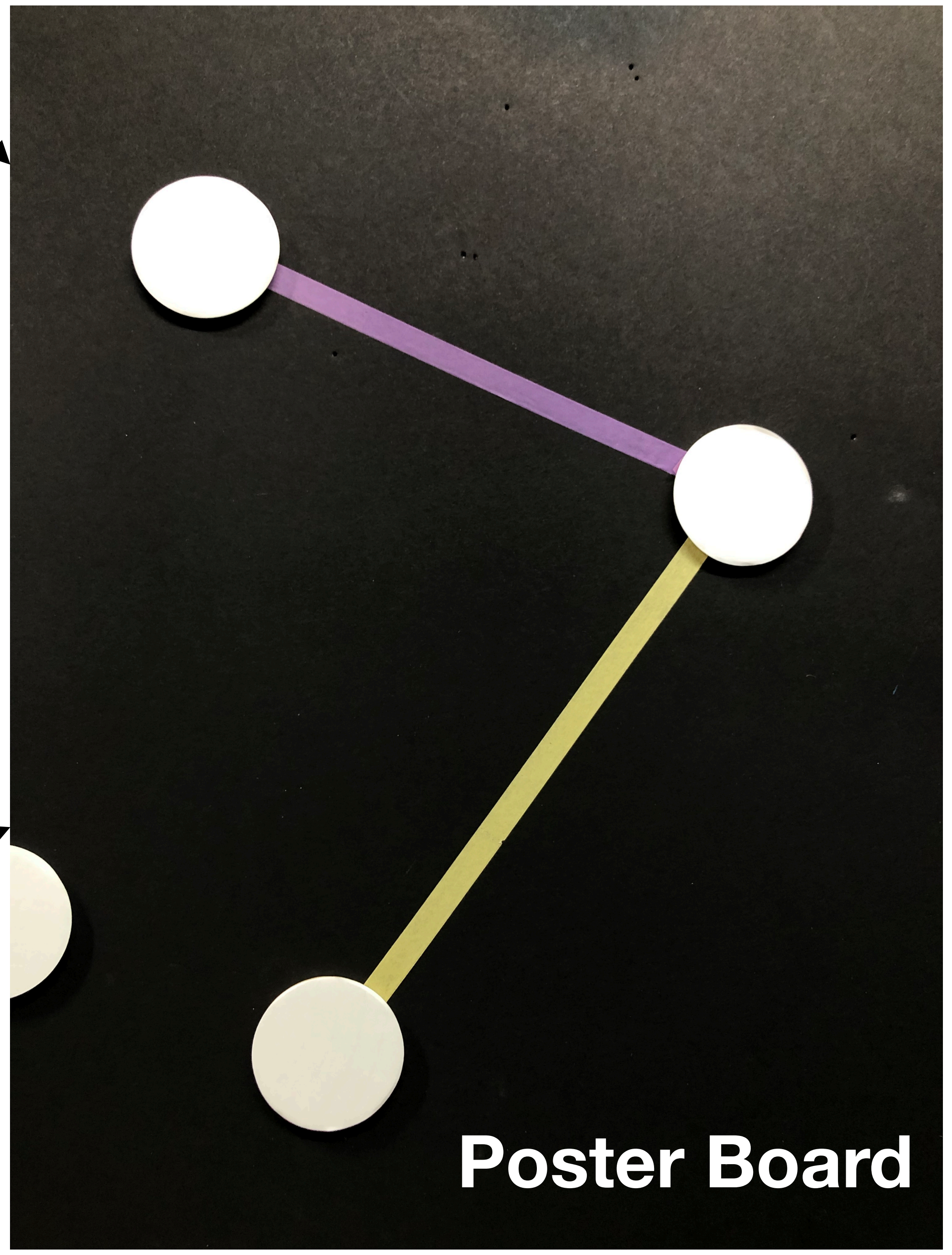
*real values except those in italics which have been reduced by a factor of 10 for the purpose of this activity



Edges

	Name	Name	Type	Frequency
1	Michelle Obama	Tina Chen	Mention	2
2	Michelle Obama	Time's Up	Mention	2
3	Michelle Obama	NowThis	Mention	2
4	Michelle Obama	Kerry Washington	Retweet	2
5	Time's Up	MeToo	Retweet	2
6	Time's Up	Tina Chen	Mention	2
7	Time's Up	Kerry Washington	Retweet	1
8	Time's Up	Justice for Migrant Women	Retweet	3
9	Tina Chen	Kerry Washington	Retweet	1
10	Tina Chen	Kerry Washington	Mention	1
11	MeToo	Monica Ramirez	Mention	1
12	MeToo	National Women's Law Center	Retweet	2
13	MeToo	Justice 4 Migrant Women	Retweet	1
14	Justice 4 Migrant Women	National Women's Law Center	Mention	1
15	Justice 4 Migrant Women	Monica Ramirez	Mention	1
16	Justice 4 Migrant Women	NowThis	Retweet	1
17	NowThis	Alexandria Ocasio-Cortez	Retweet	2

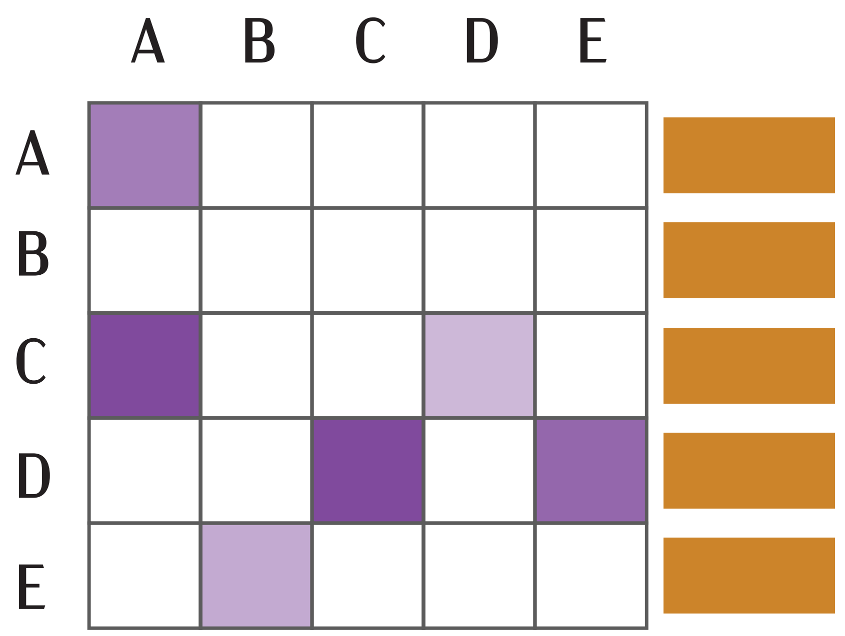
Washi Tape



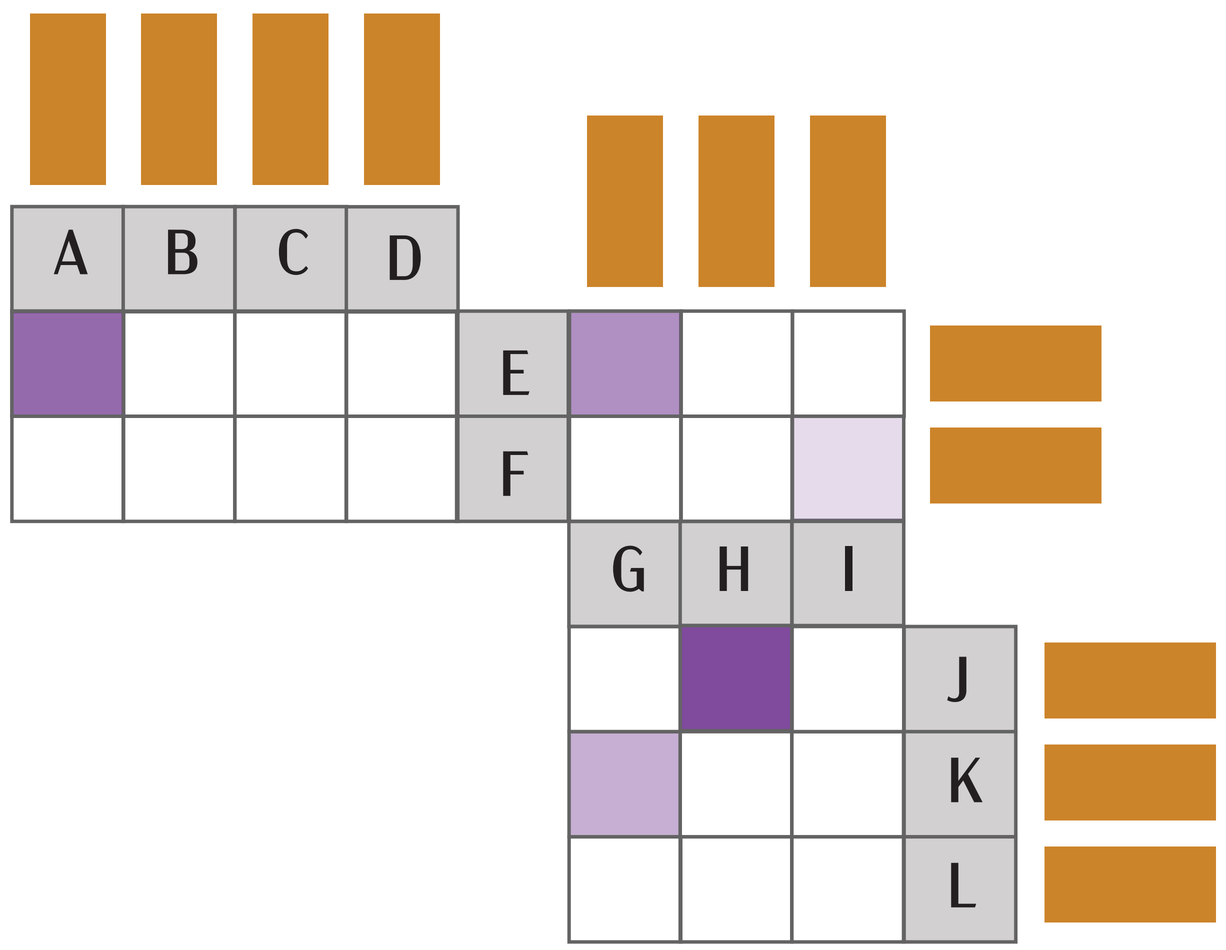
20 minutes

Show and Tell

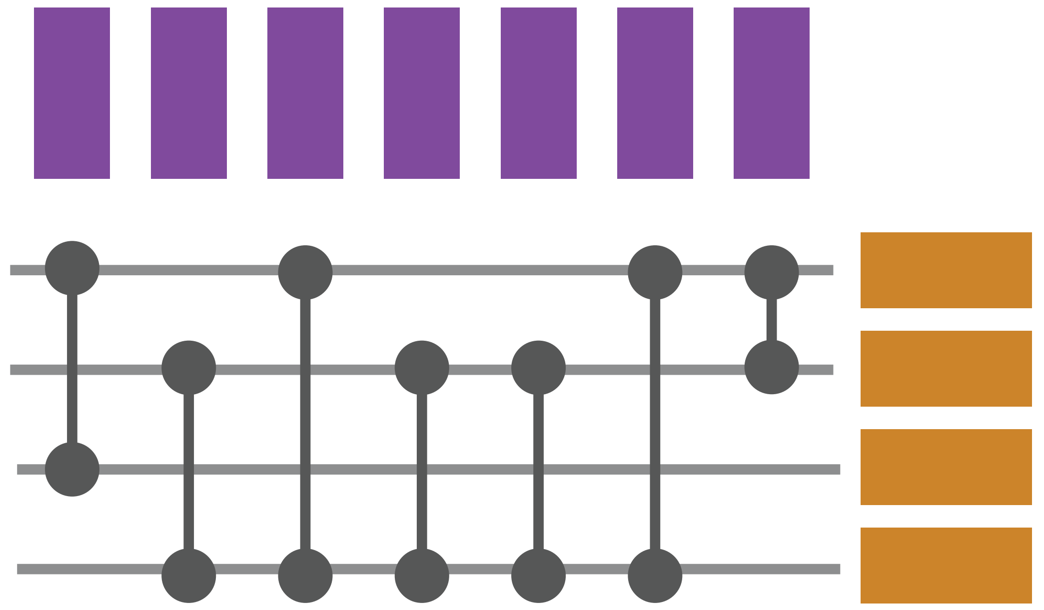
Tabular Layouts



Adjacency Matrix

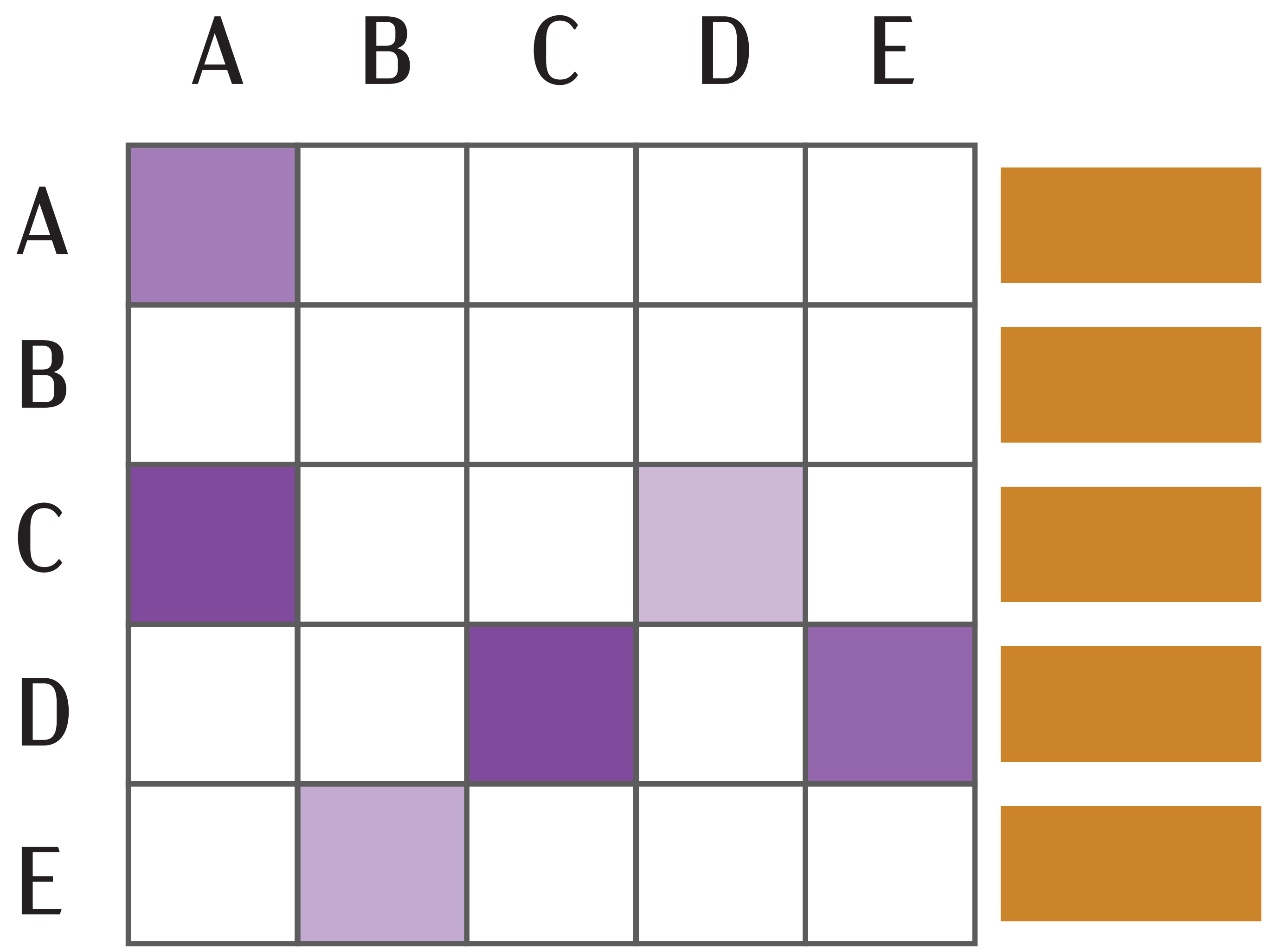


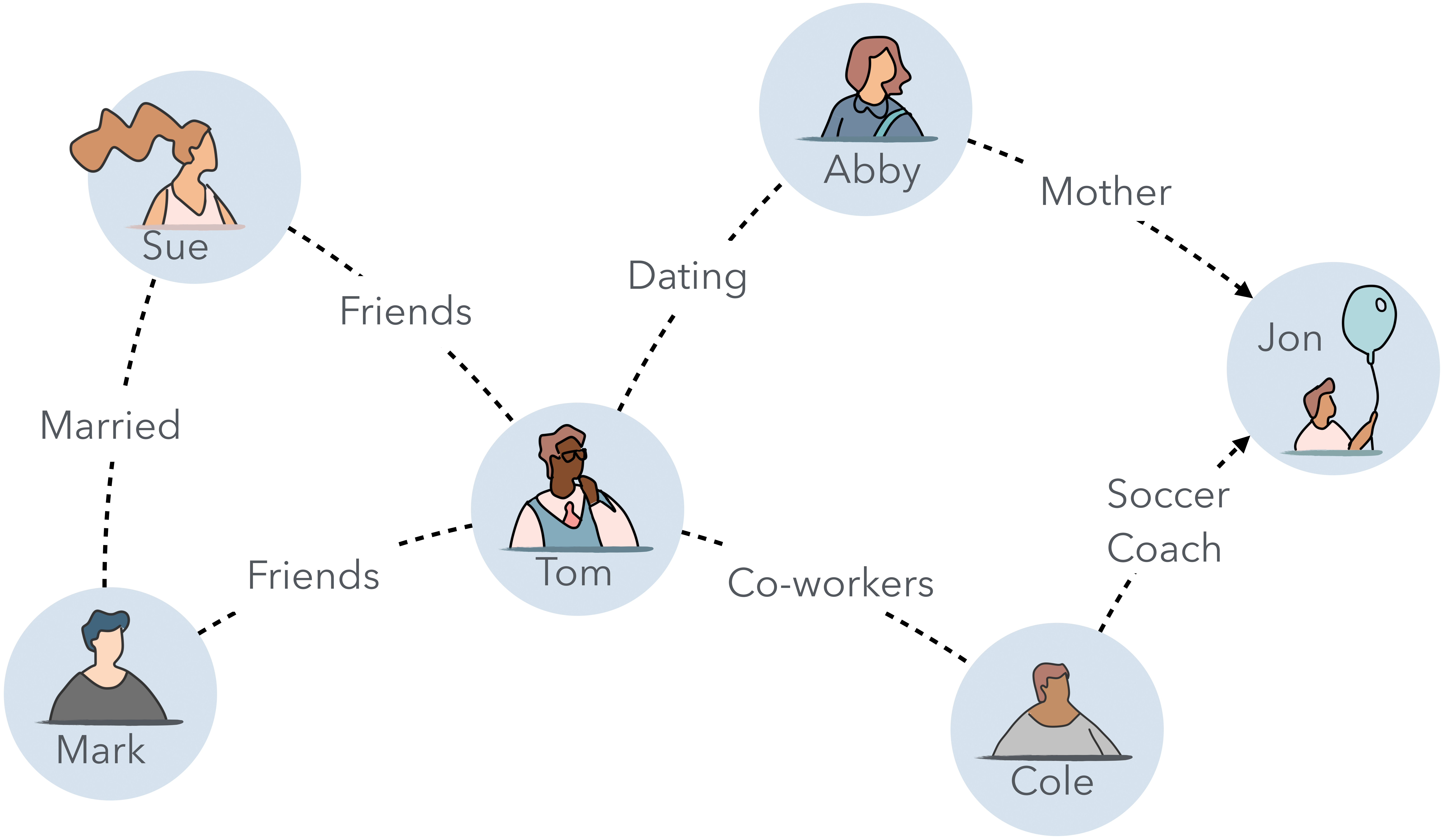
Quilts

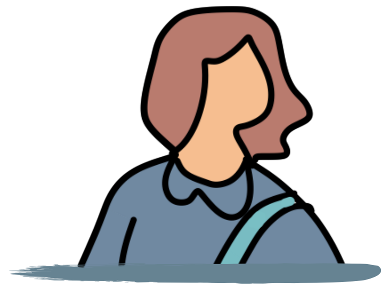


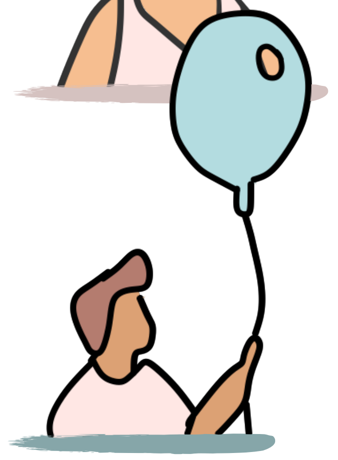
BioFabric

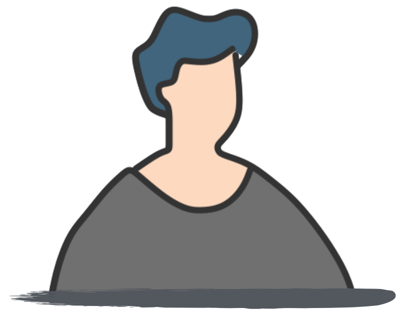
Adjacency Matrix

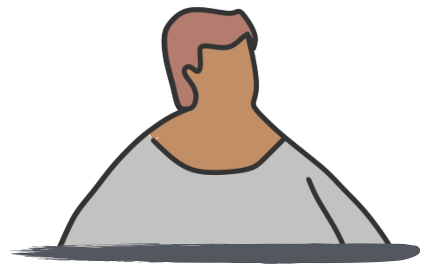


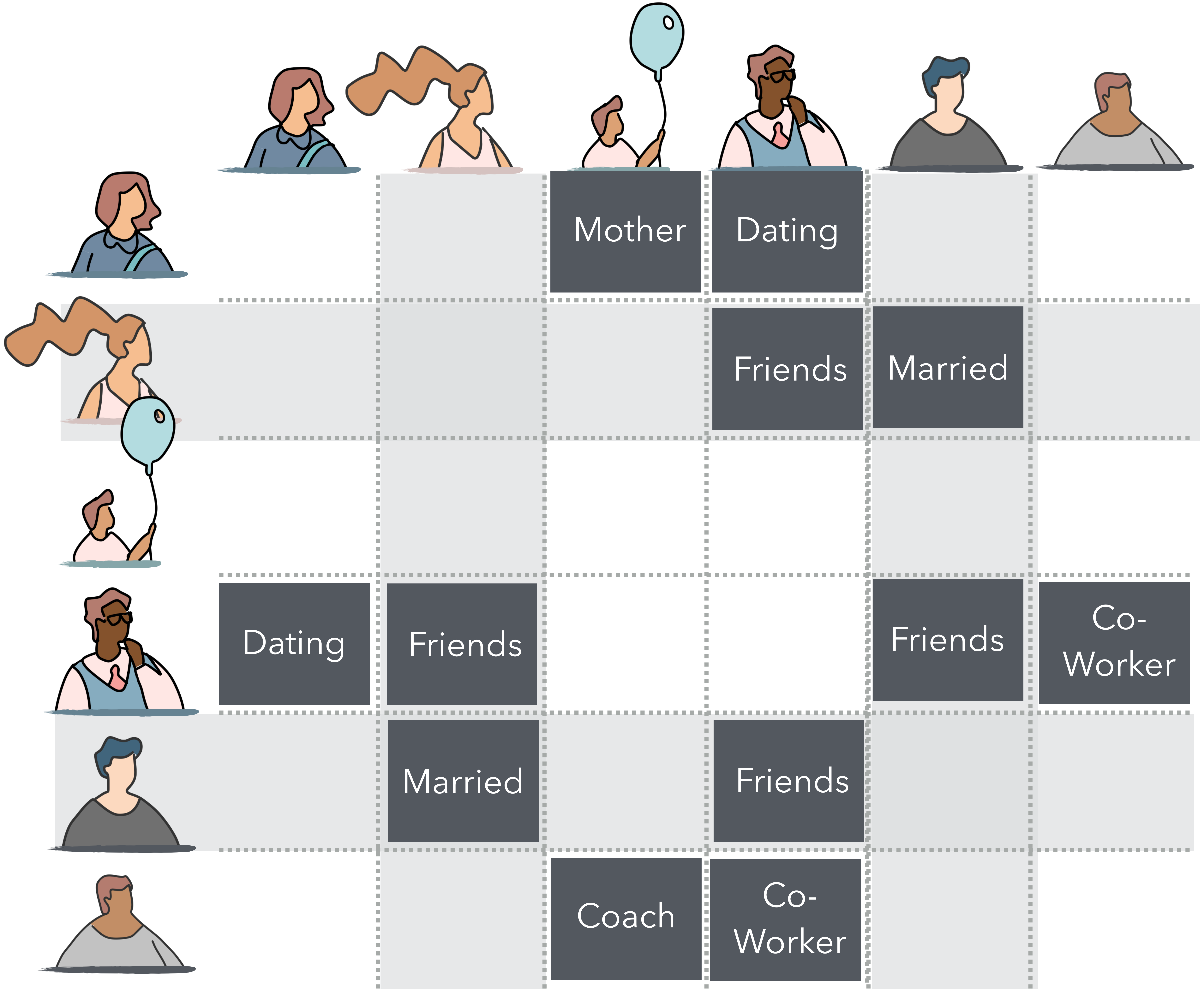

Sue
Abby
Mother
Friends
Dating
Jon
Married
Tom
Soccer
Coach
Friends
Co-workers
Mark
Cole



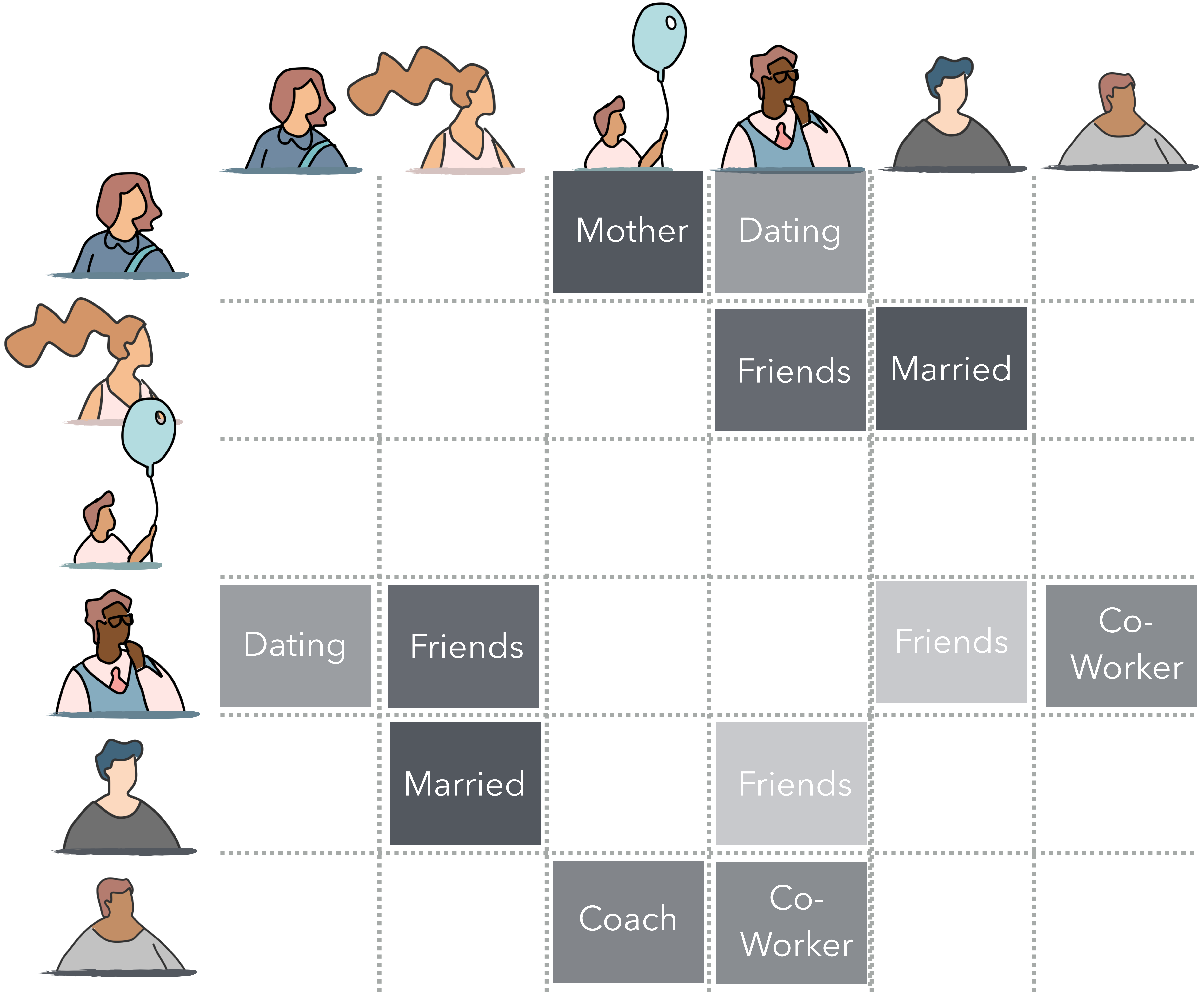




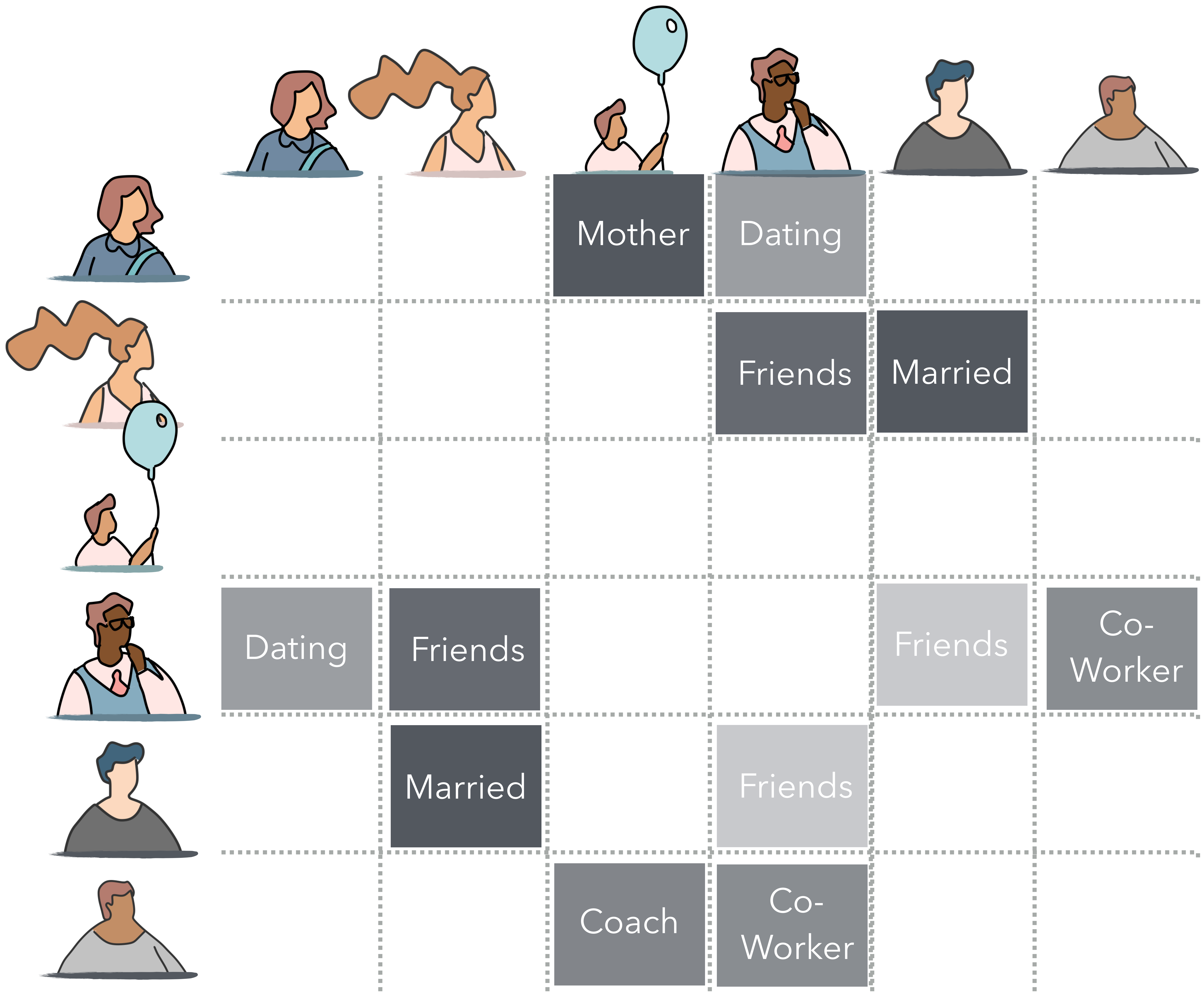




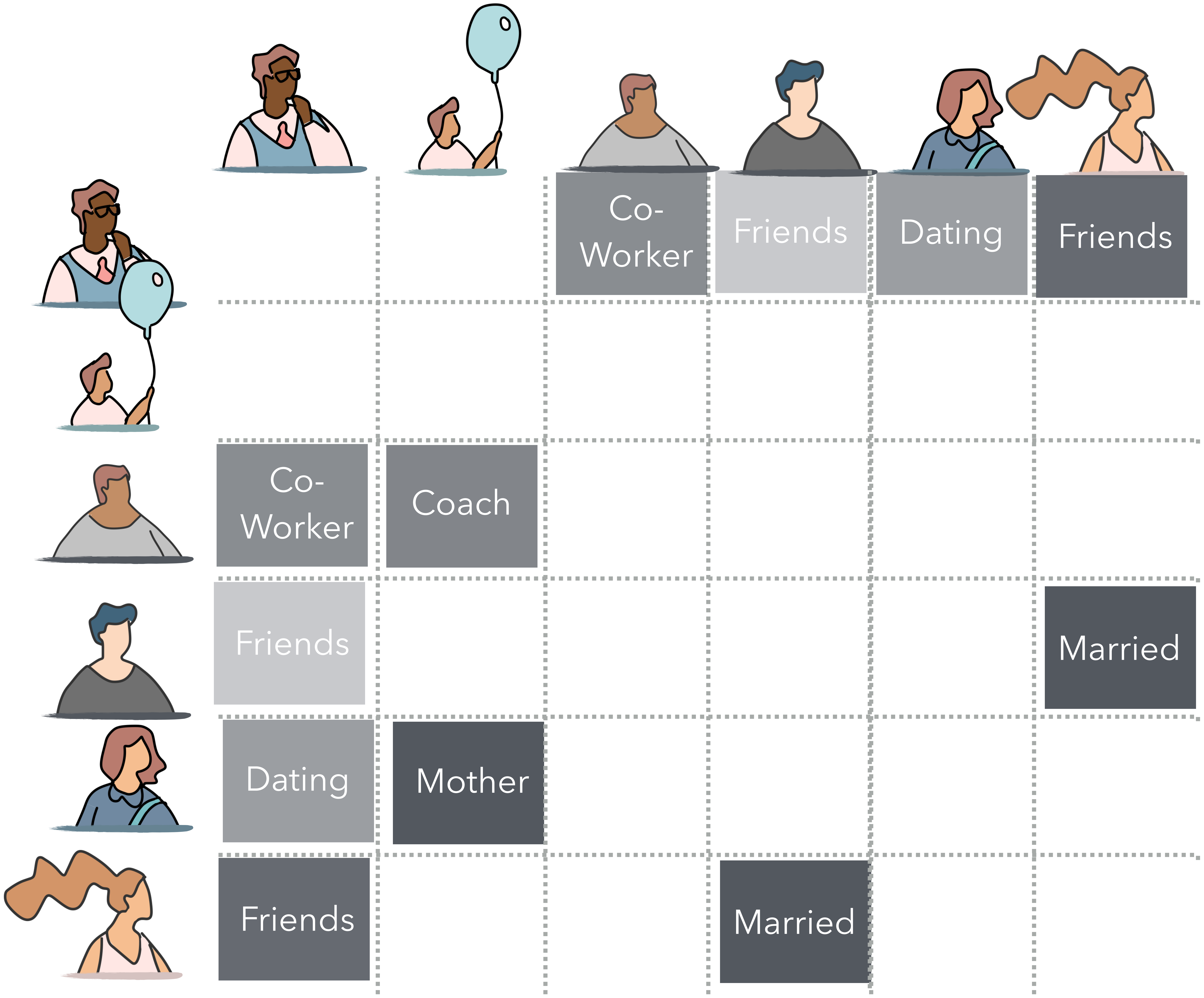
Mother
Dating
Friends
Married
Dating
Friends
Friends
Co-
Worker
Married
Friends
Coach
Co-
Worker



Mother
Dating
Friends
Married
Dating
Friends
Friends
Co-Worker
Married
Friends
Coach
Co-Worker

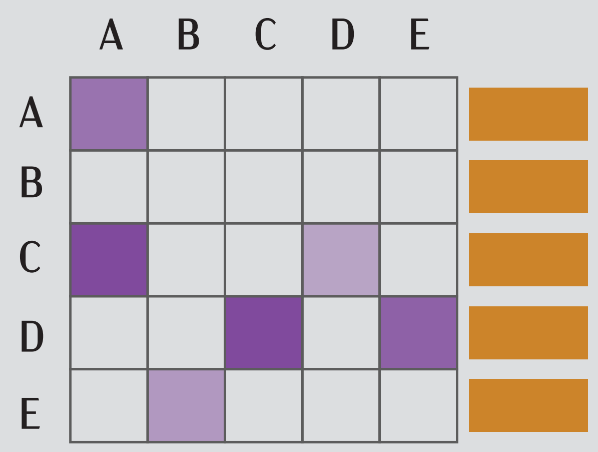


Name	Beverage	Day 1
Abby	Port	1
Sue	Coke	0
Jon	Coke	4
Tom	Beer	5
Mark	Beer	2
Cole	Port	3

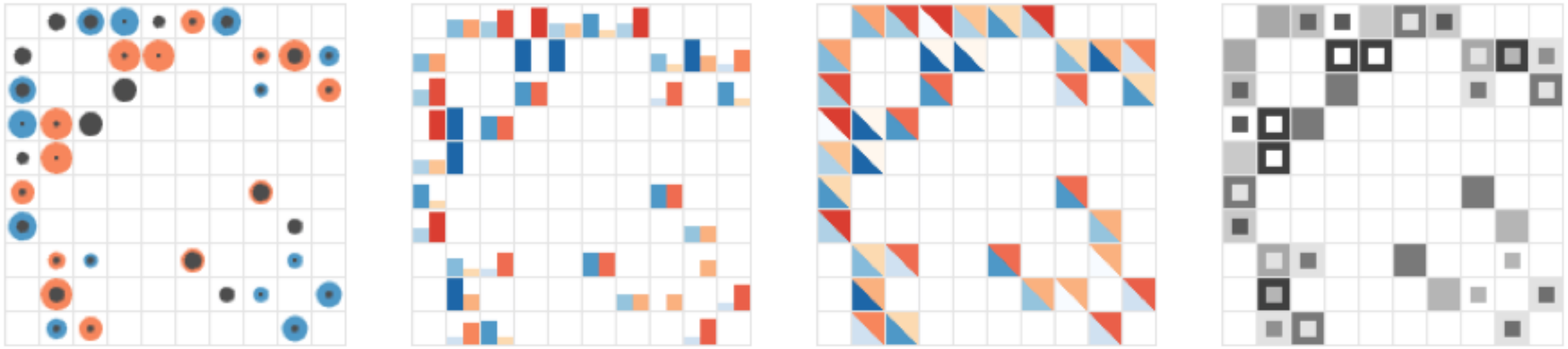


Name	Beverage	Day 1
Tom	Beer	5
Jon	Coke	4
Cole	Port	3
Mark	Beer	2
Abby	Port	1
Sue	Coke	0

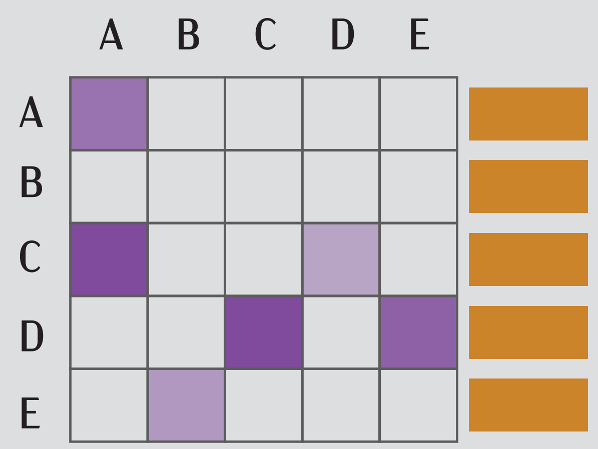
Moritz Stefaner, Musli Ingredient Network. https://truth-and-beauty.net/projects/muesli-ingredient-network



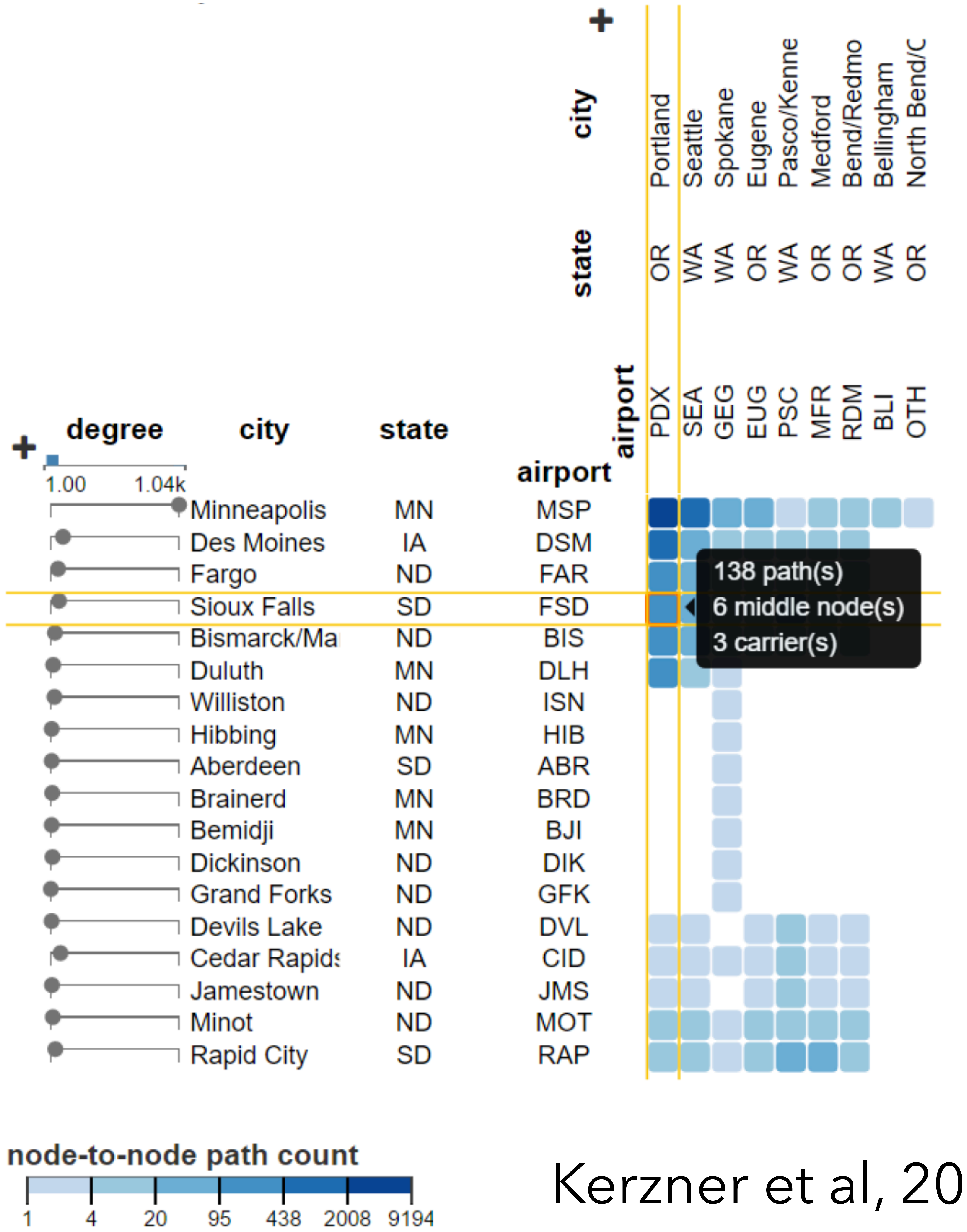
Adjacency Matrix



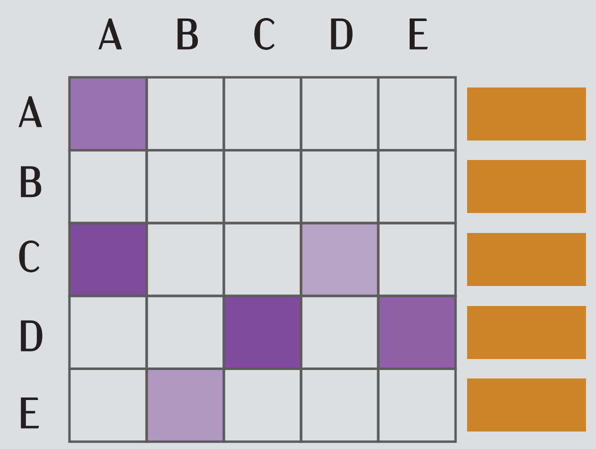
Alper et al, 2013



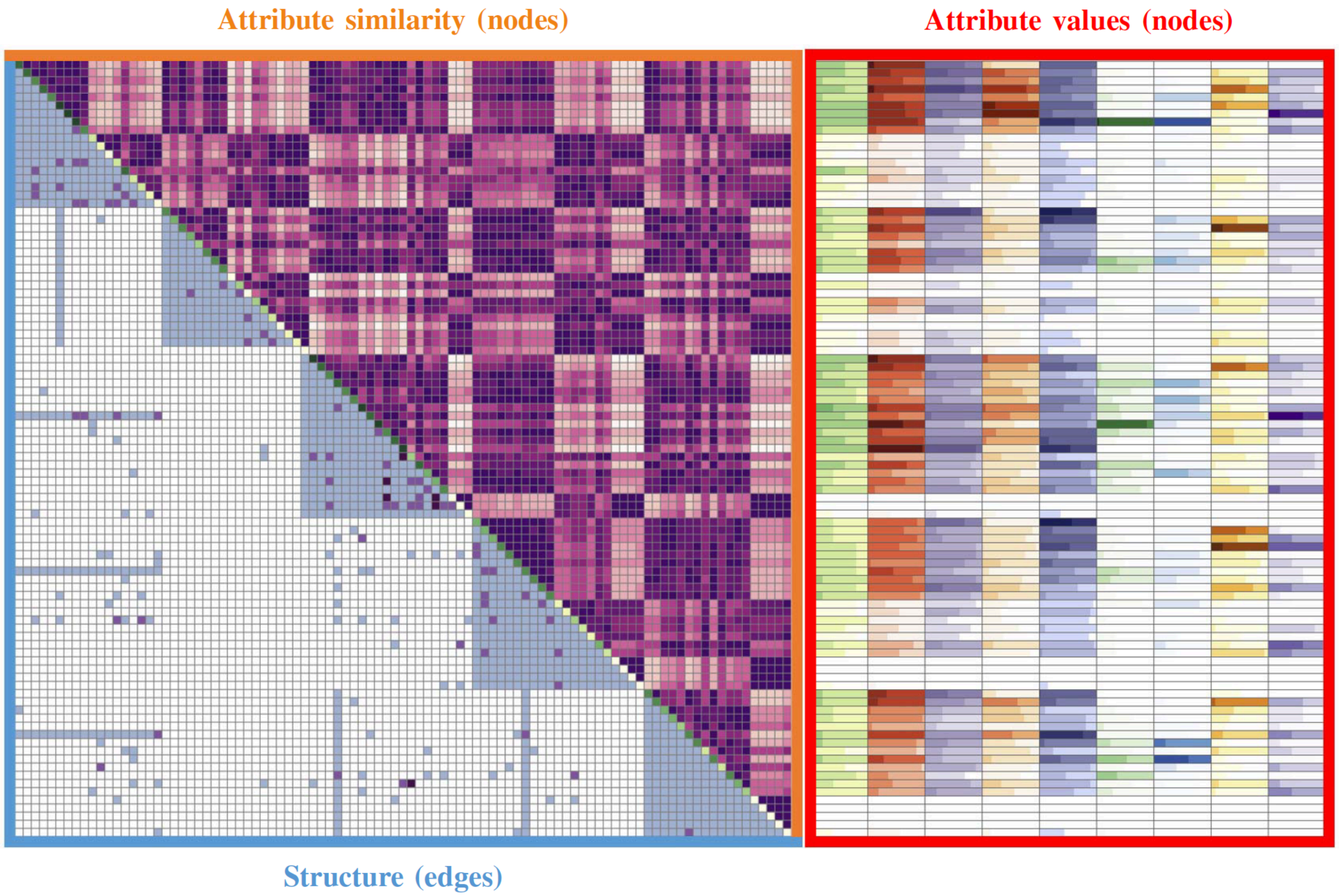
Adjacency Matrix

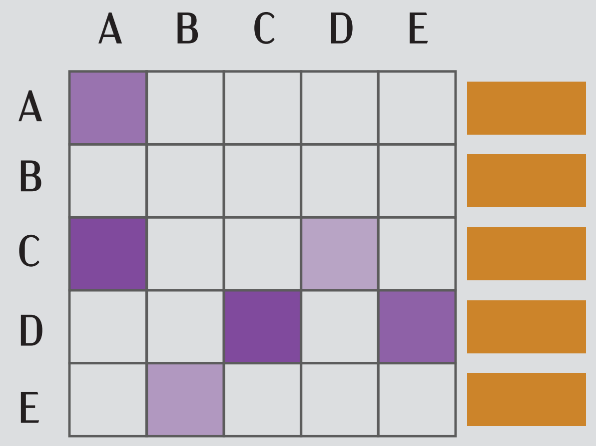


Kerzner et al, 2017



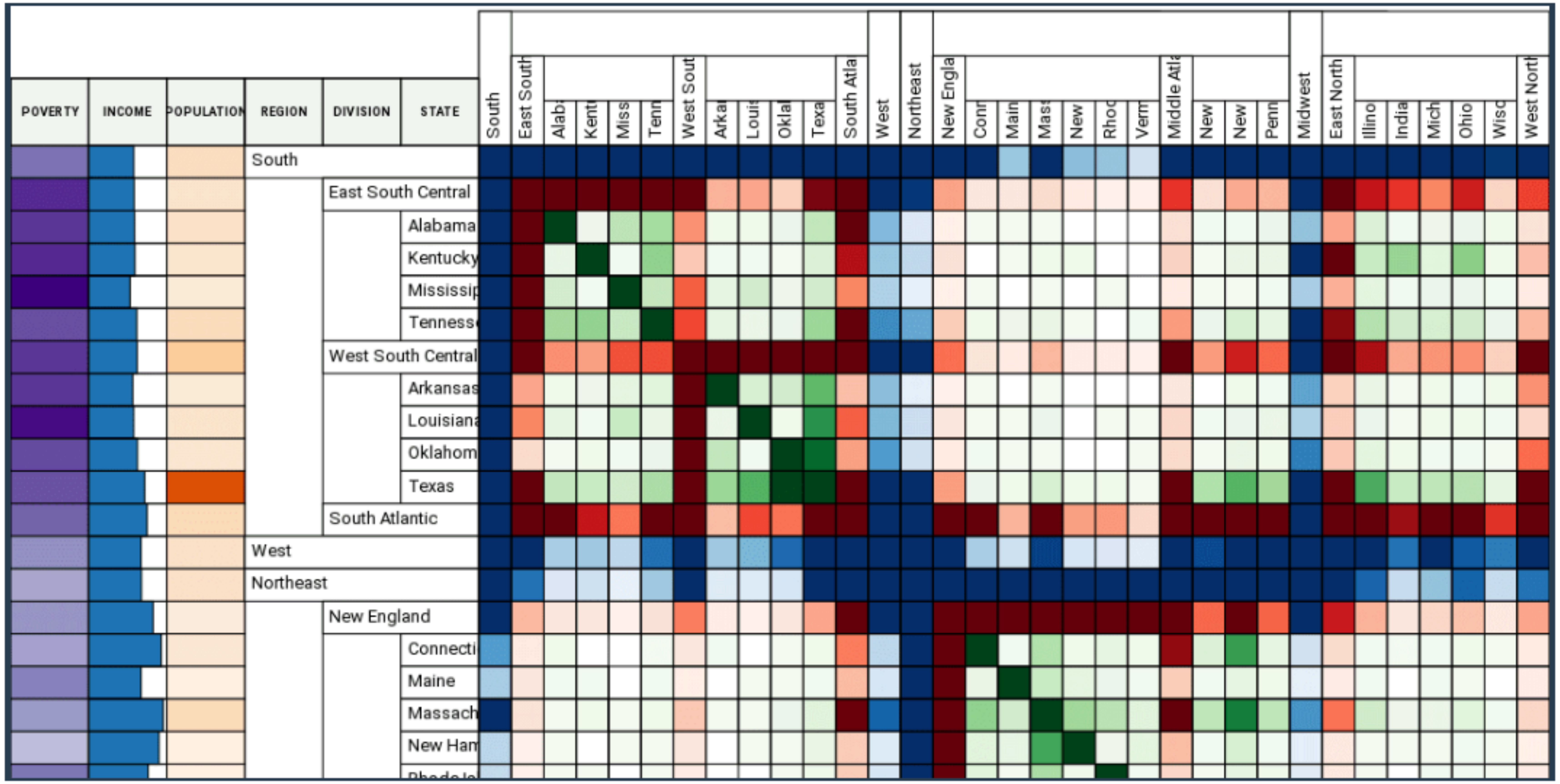
Adjacency Matrix

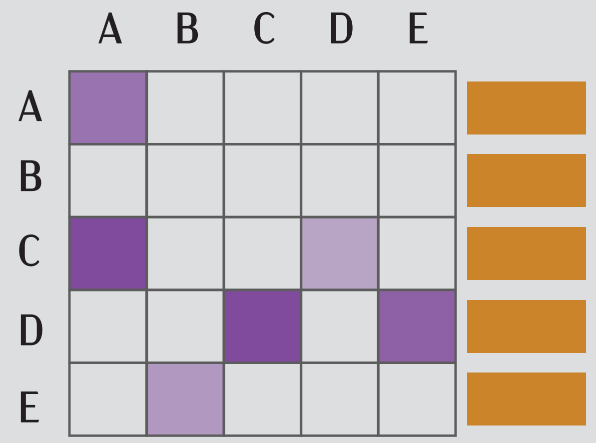




Adjacency Matrix

Berger et al, 2019

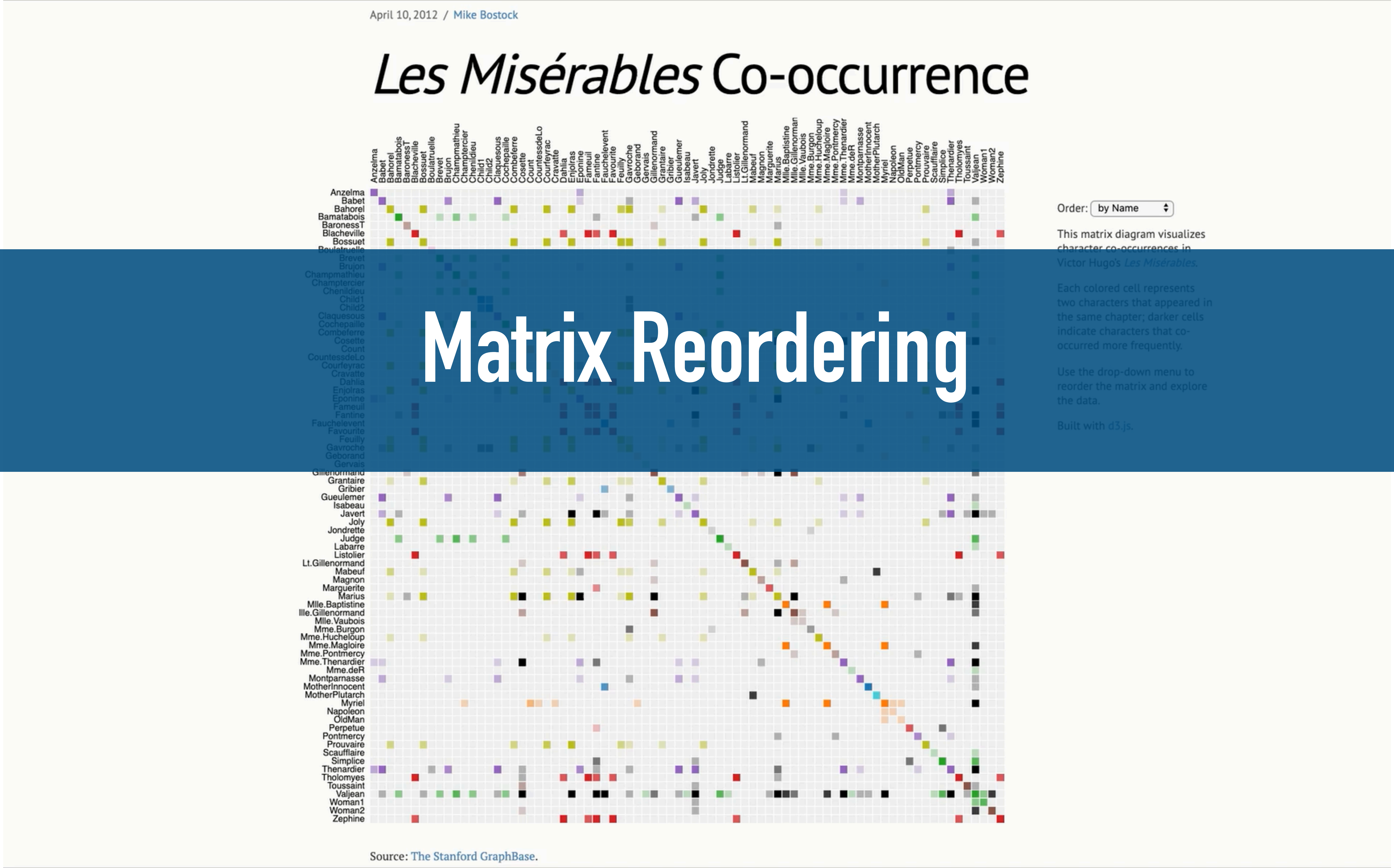




Adjacency Matrix

Safarli and Lex, 2019

Matrix Reordering



Reorder.js

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Edit | New Page

Jean-Daniel Fekete edited this page on Apr 23, 2015 · 2 revisions

Reorder.js is a library to reorder tables and graph/networks.

Resources

- Introduction
- API Reference

Browser / Platform Support

Reorder.js is mainly developed on Chrome and Node.js. Use `npm install reorder.js` to install, and `require("reorder")` to load.

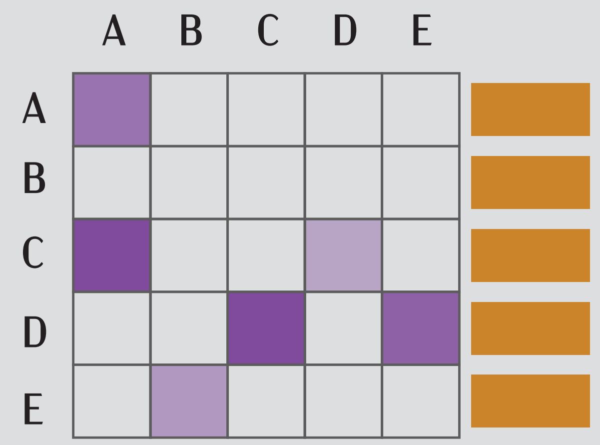
Installing

Download the latest version here:

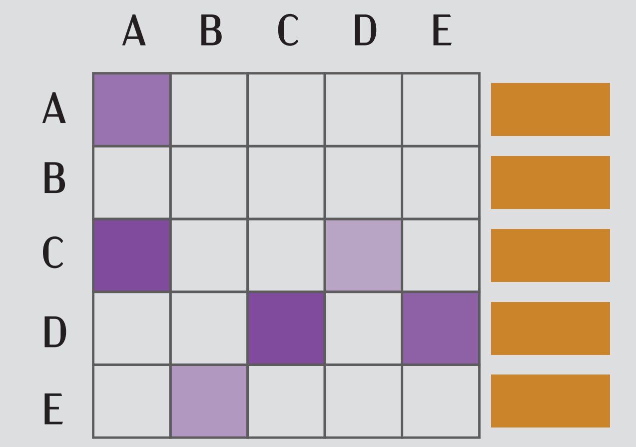
- https://github.com/jdfekete/reorder.js/releases

+ Add a custom footer

+ Add a custom sidebar



Adjacency Matrix



Adjacency Matrix

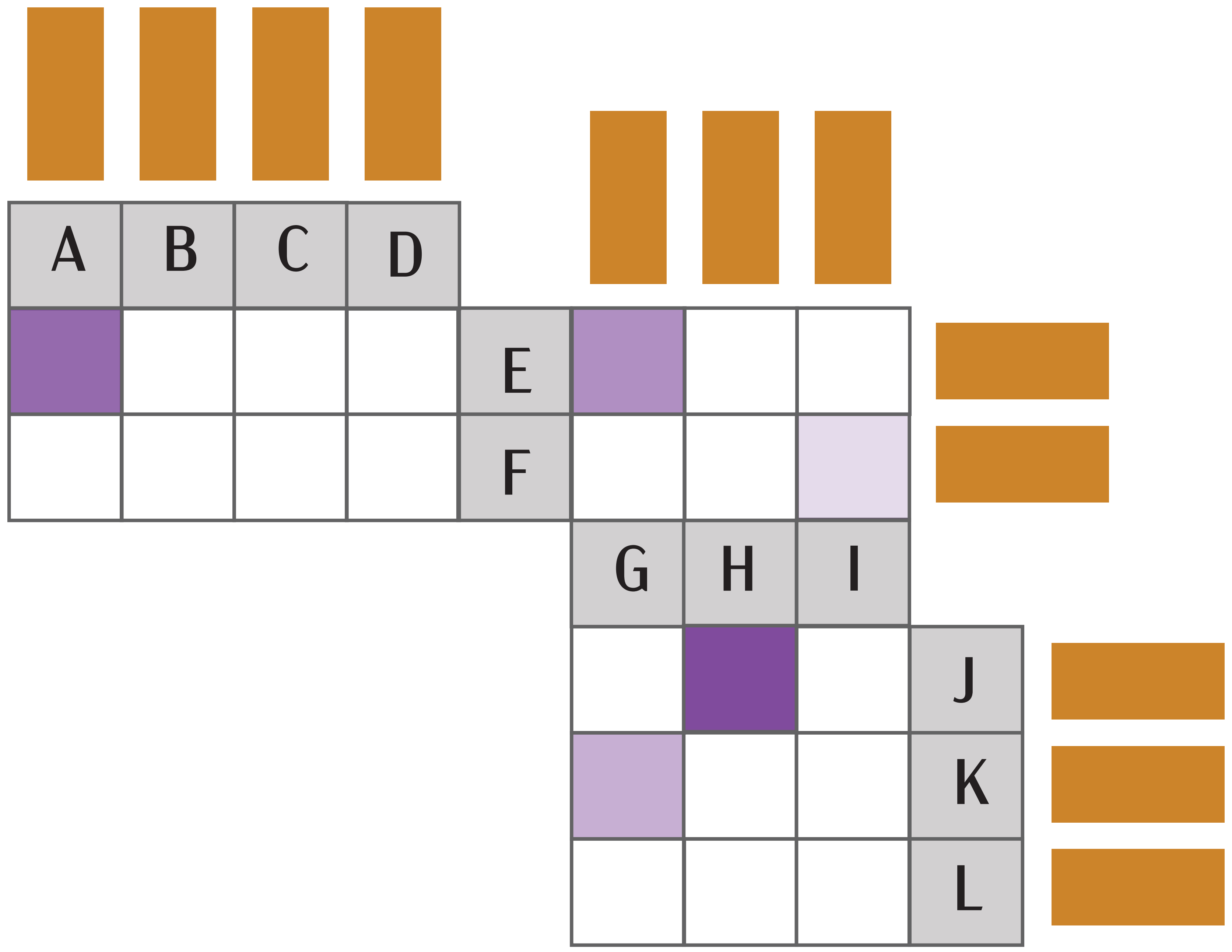
Ideal for dense and completely connected networks

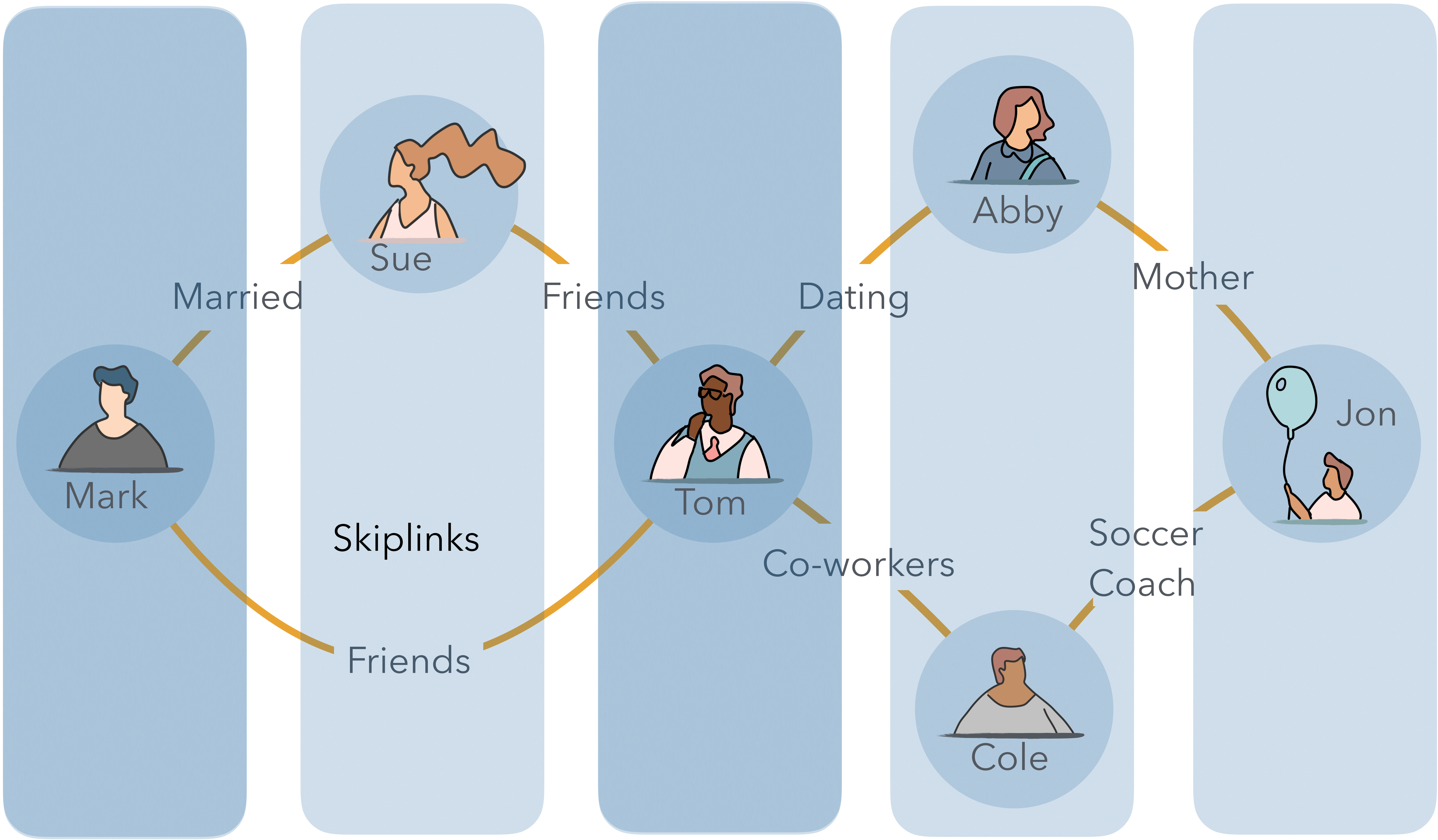
Requires quadratic space with respect to the number of nodes.

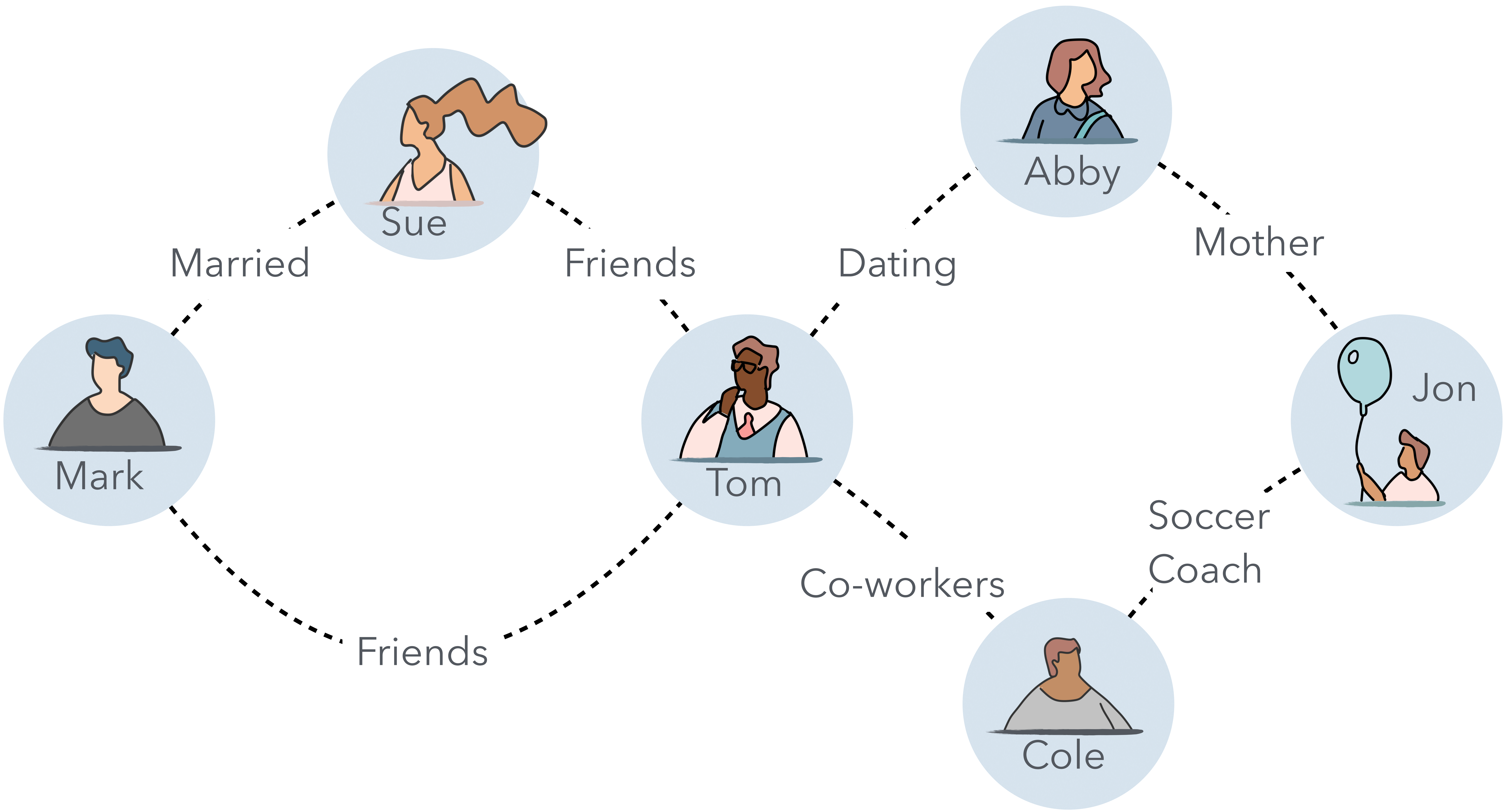
Complexity of choosing the right reordering algorithm

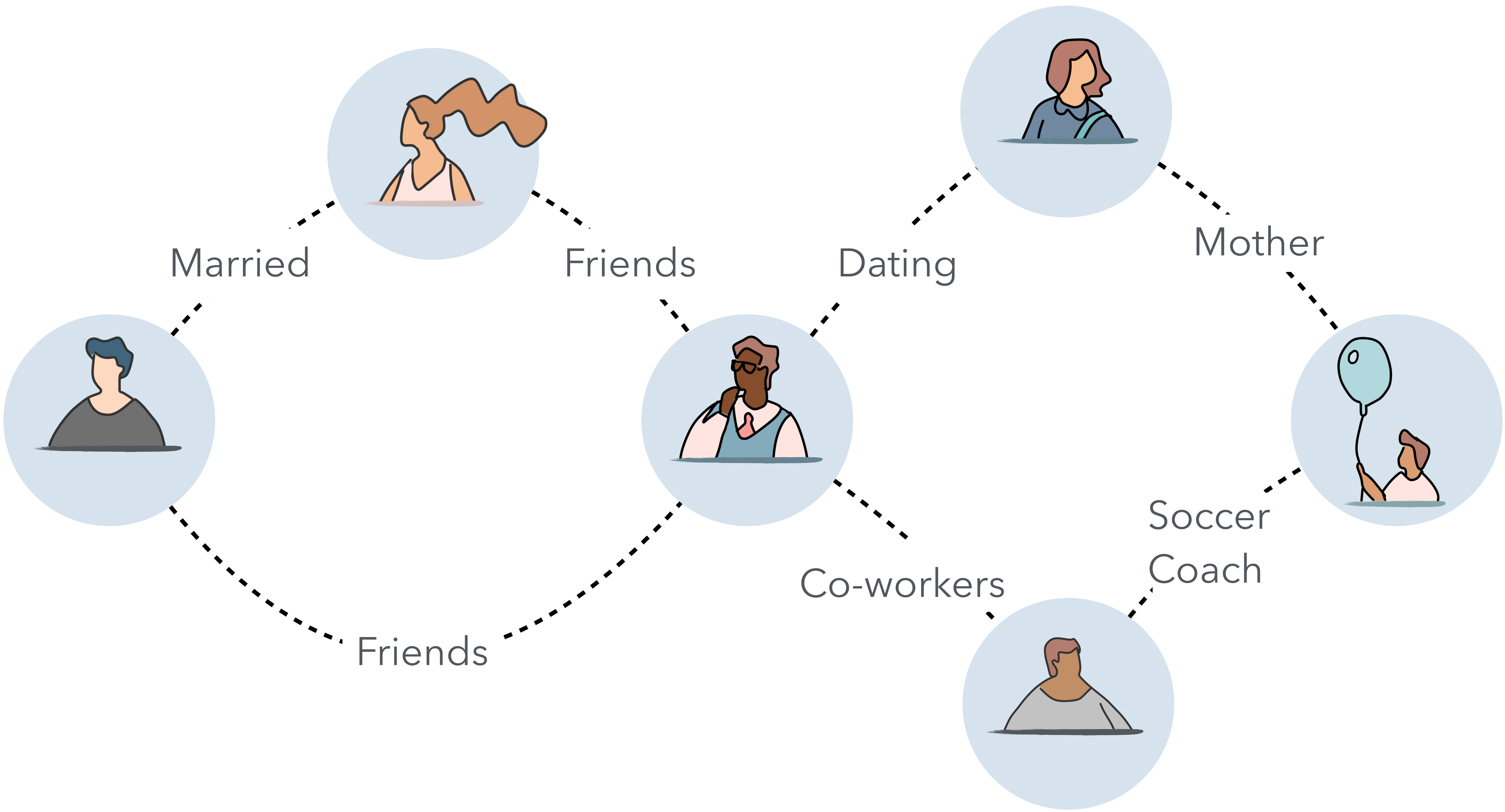
Recommended for smaller, complex and dense networks with rich node and/or edge attributes, for all tasks except for those involving paths

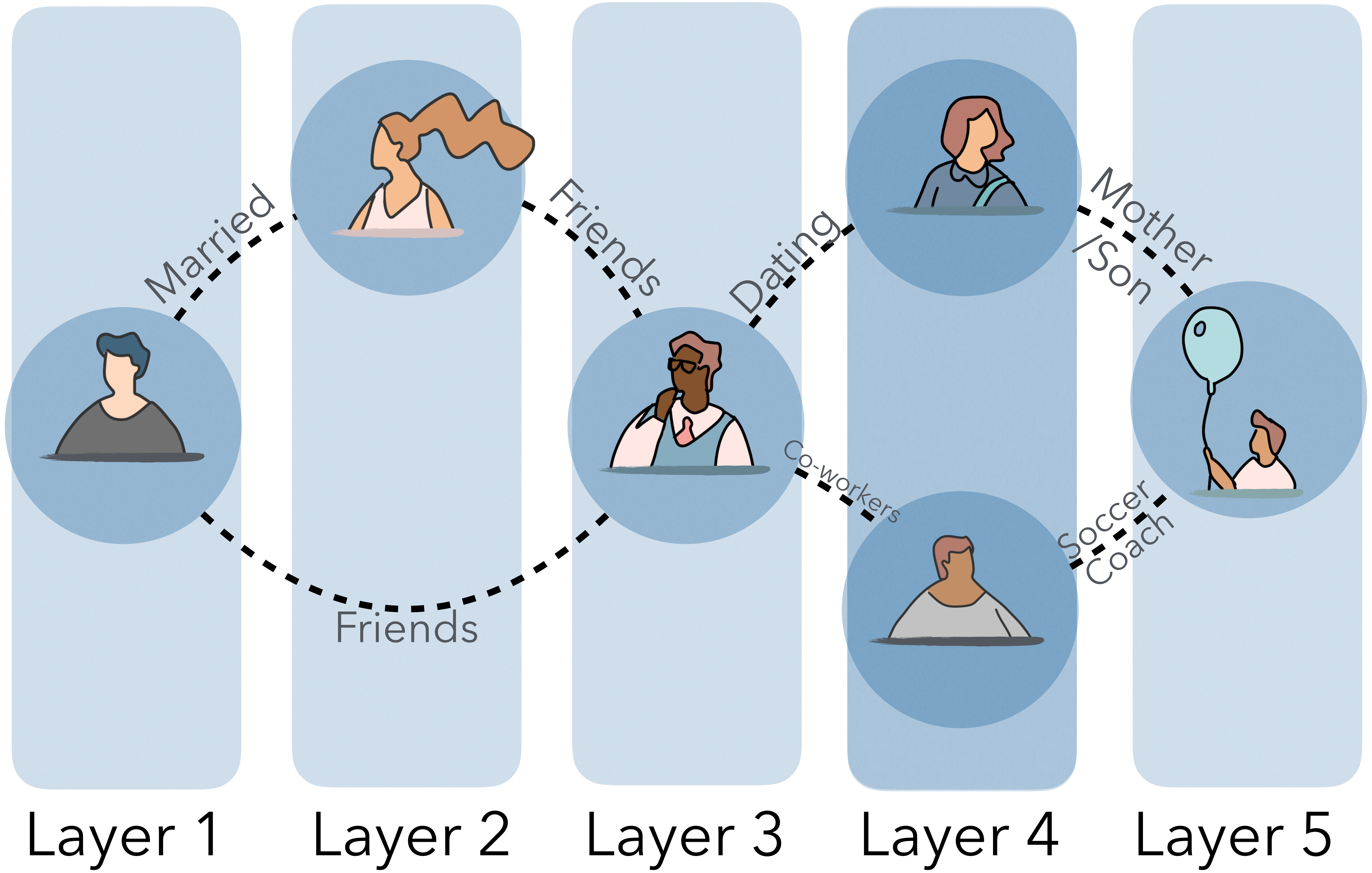
Quilts

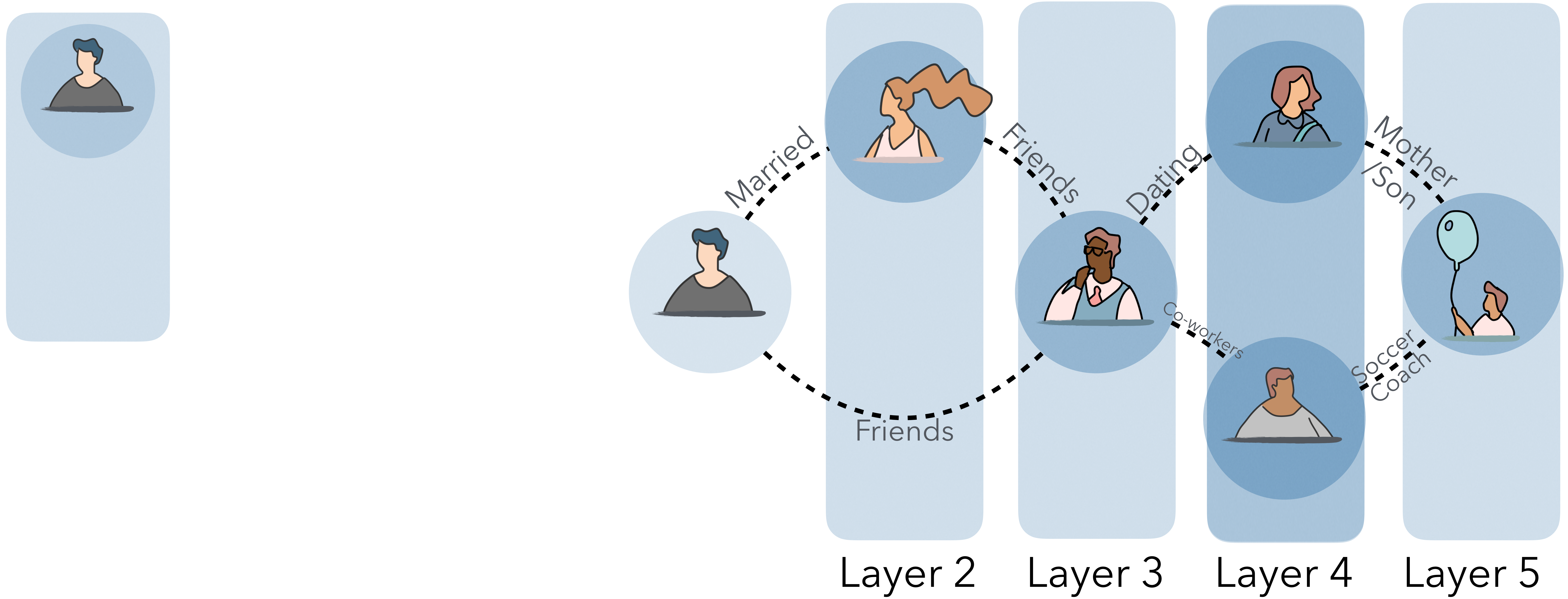



Sue
Abby
Married
Friends
Dating
Mother
Mark
Tom
Jon
Skiplinks
Co-workers
Soccer
Coach
Friends
Cole

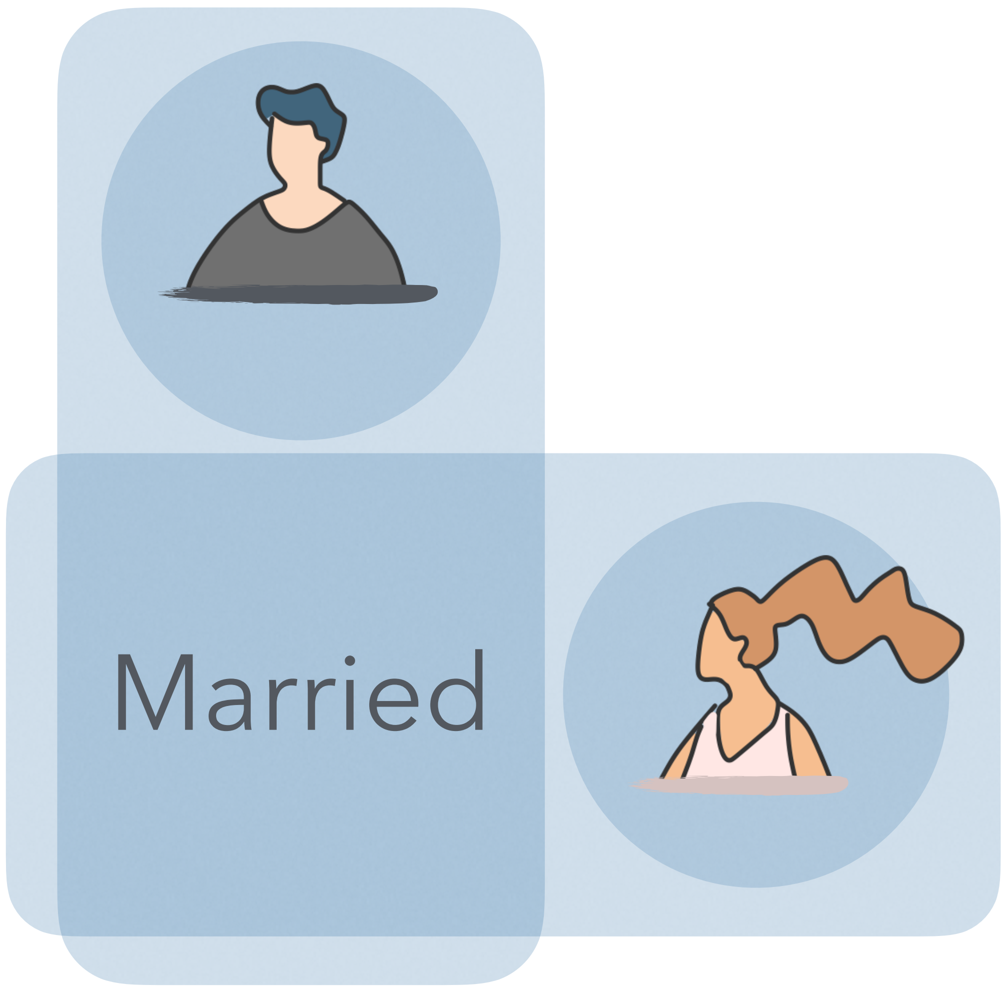

Sue
Abby
Married
Friends
Dating
Mother
Mark
Tom
Jon
Soccer Coach
Co-workers
Friends
Cole

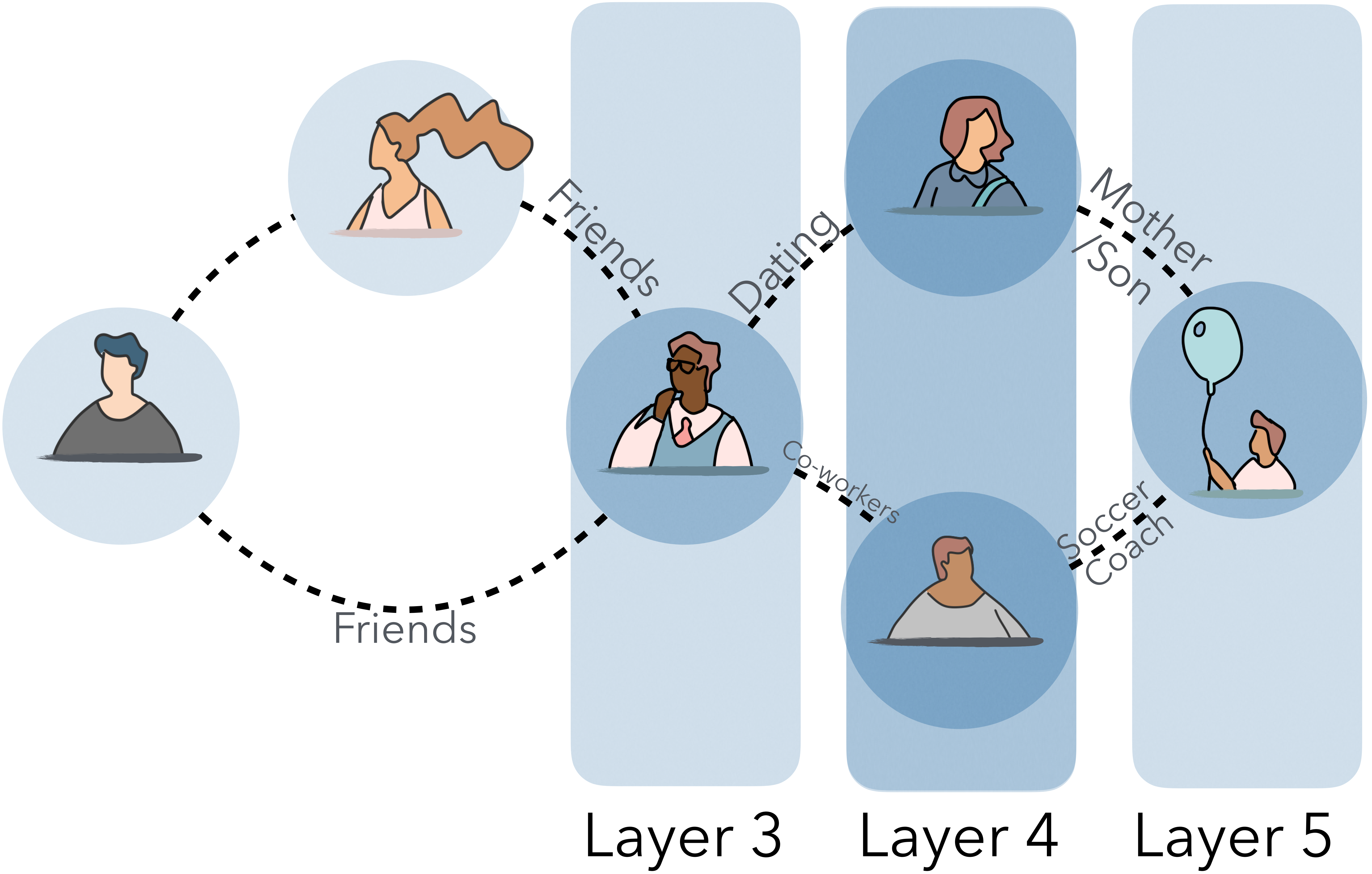

Married
Friends
Dating
Mother
Soccer
Coach
Co-workers
Friends

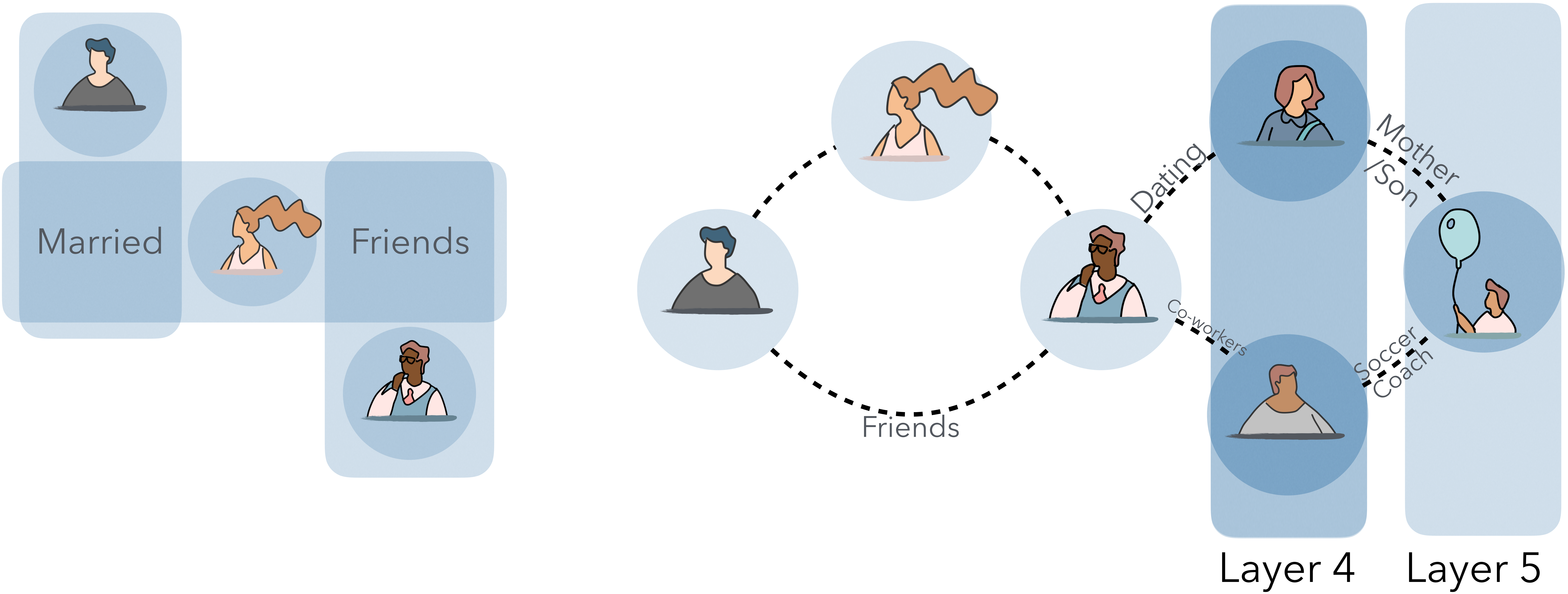

Married
Friends
Dating
Mother
/Son
Co-workers
Soccer
Coach
Friends
Layer 1
Layer 2
Layer 3
Layer 4
Layer 5



Married
Friends
Dating
Mother /Son
Co-workers
Soccer Coach
Friends
Layer 2
Layer 3
Layer 4
Layer 5


Married


Friends
Friends
Dating
Co-workers
Mother
/Son
Soccer
Coach
Layer 3
Layer 4
Layer 5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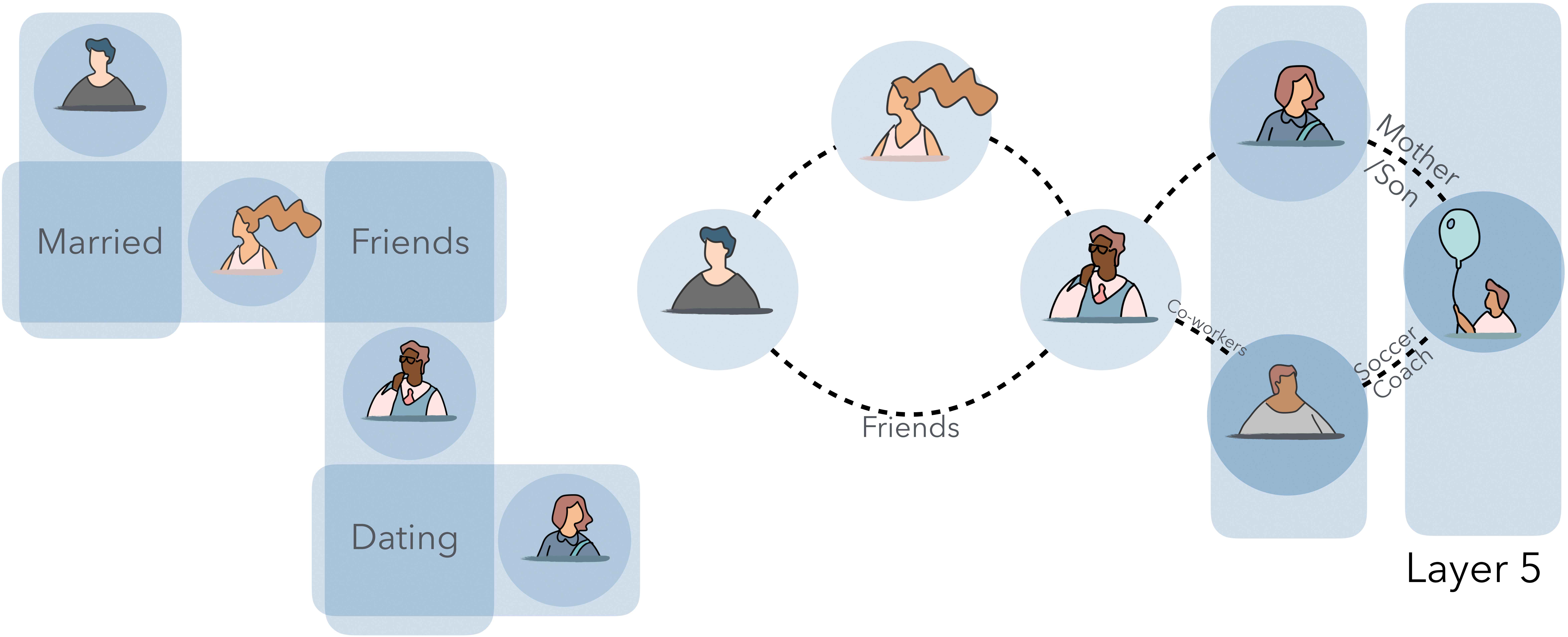
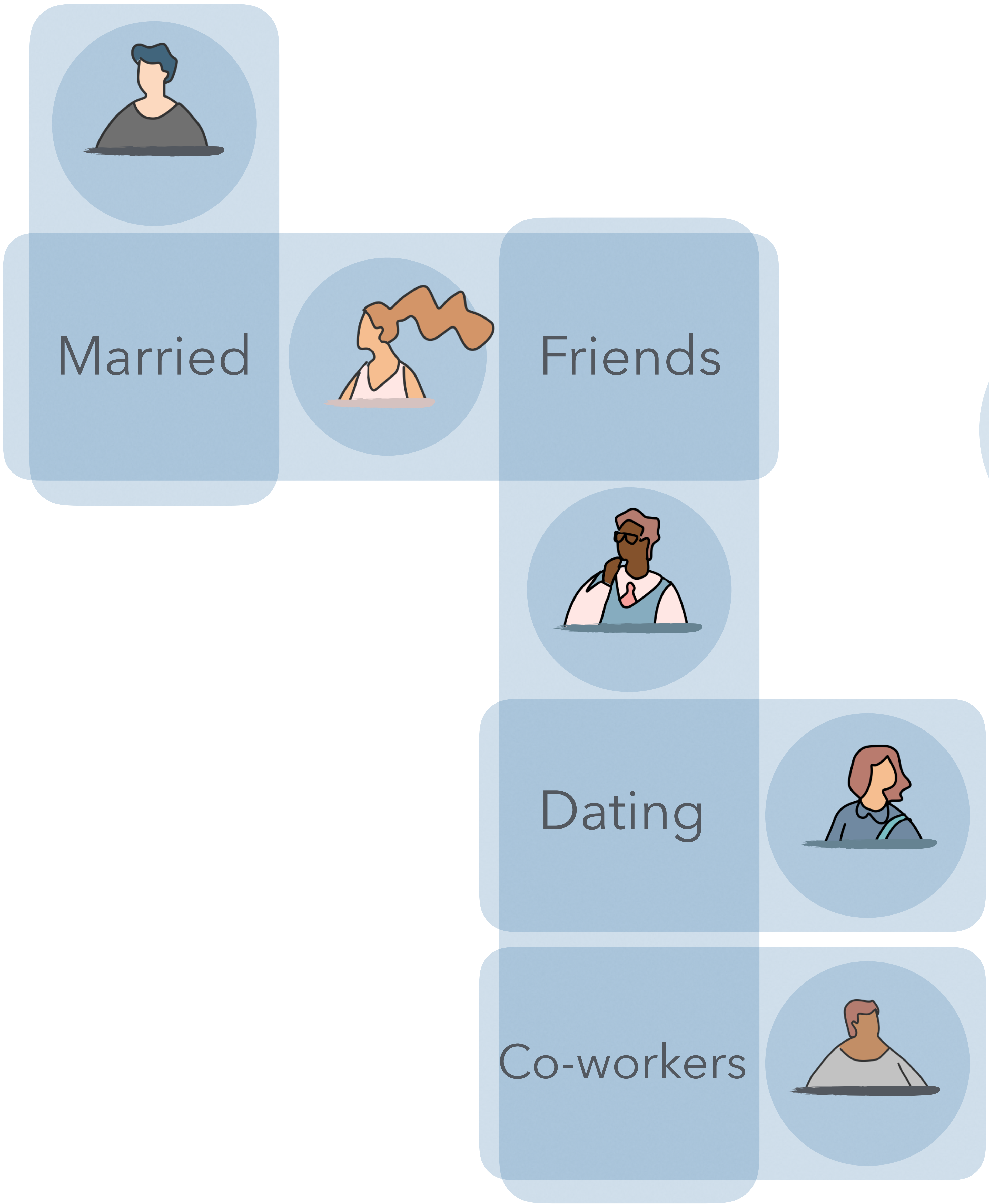
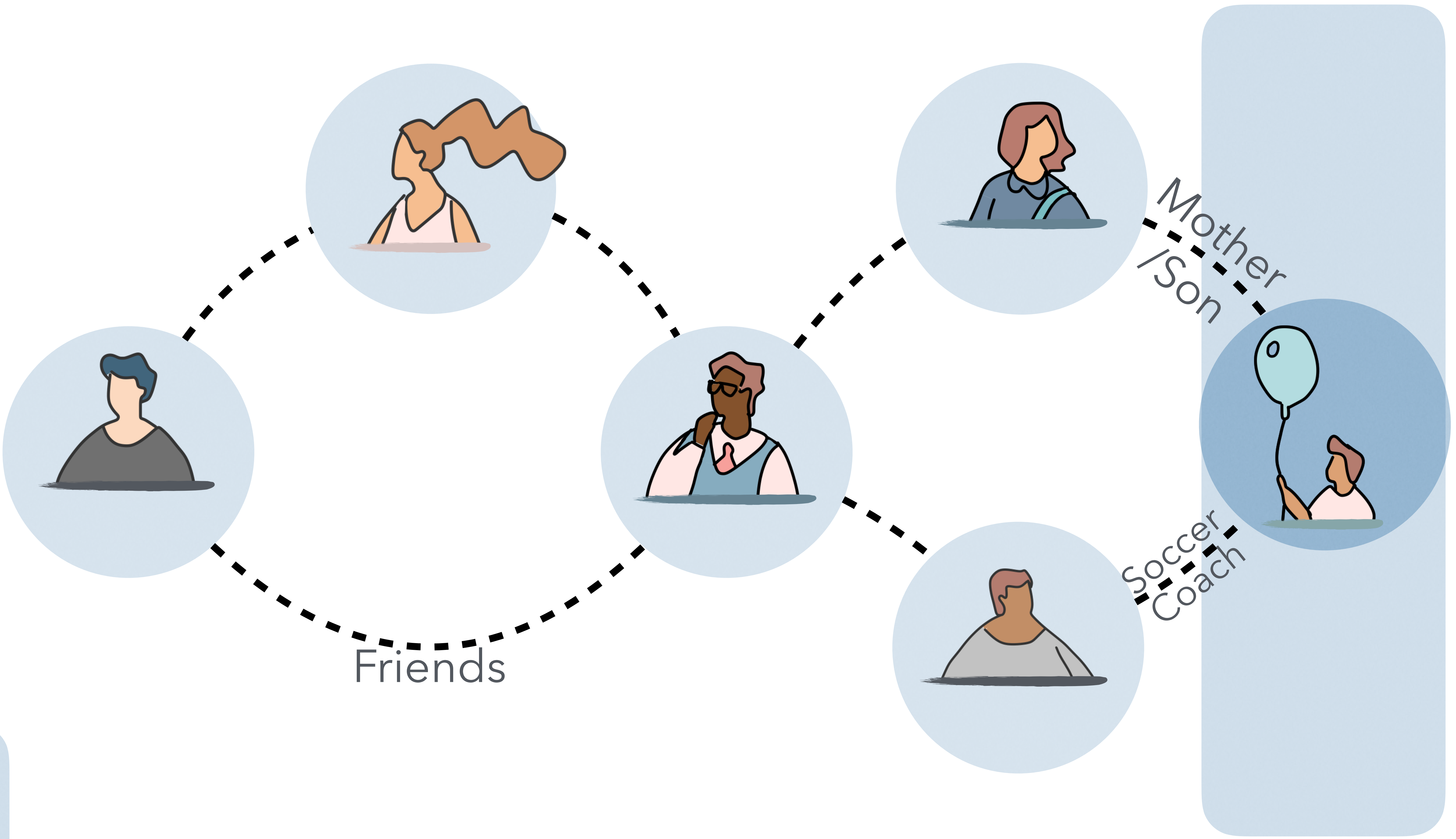
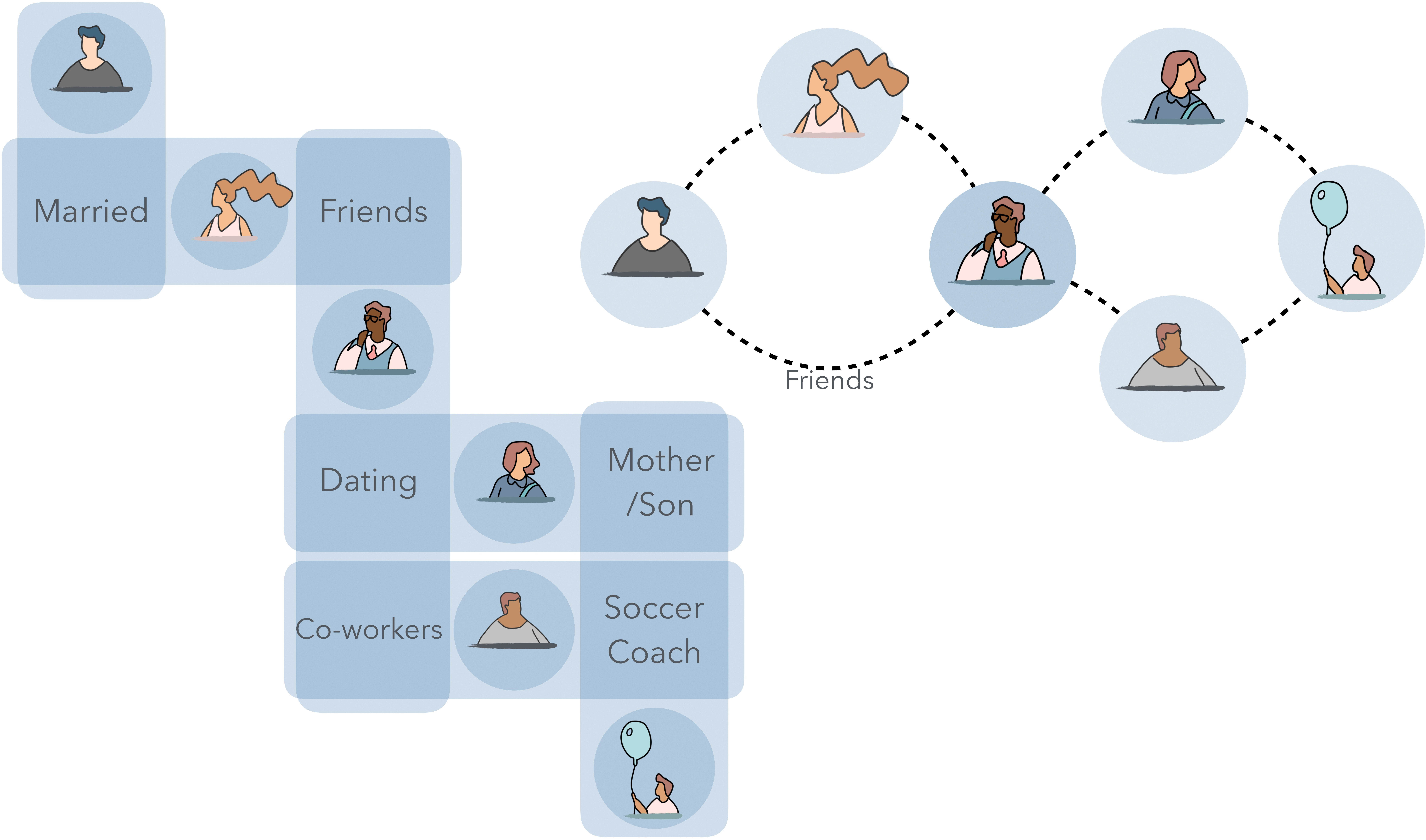
Friends
Dating
Mother
/Son
Co-workers
Soccer
Coach
Friends
Layer 4
Layer 5

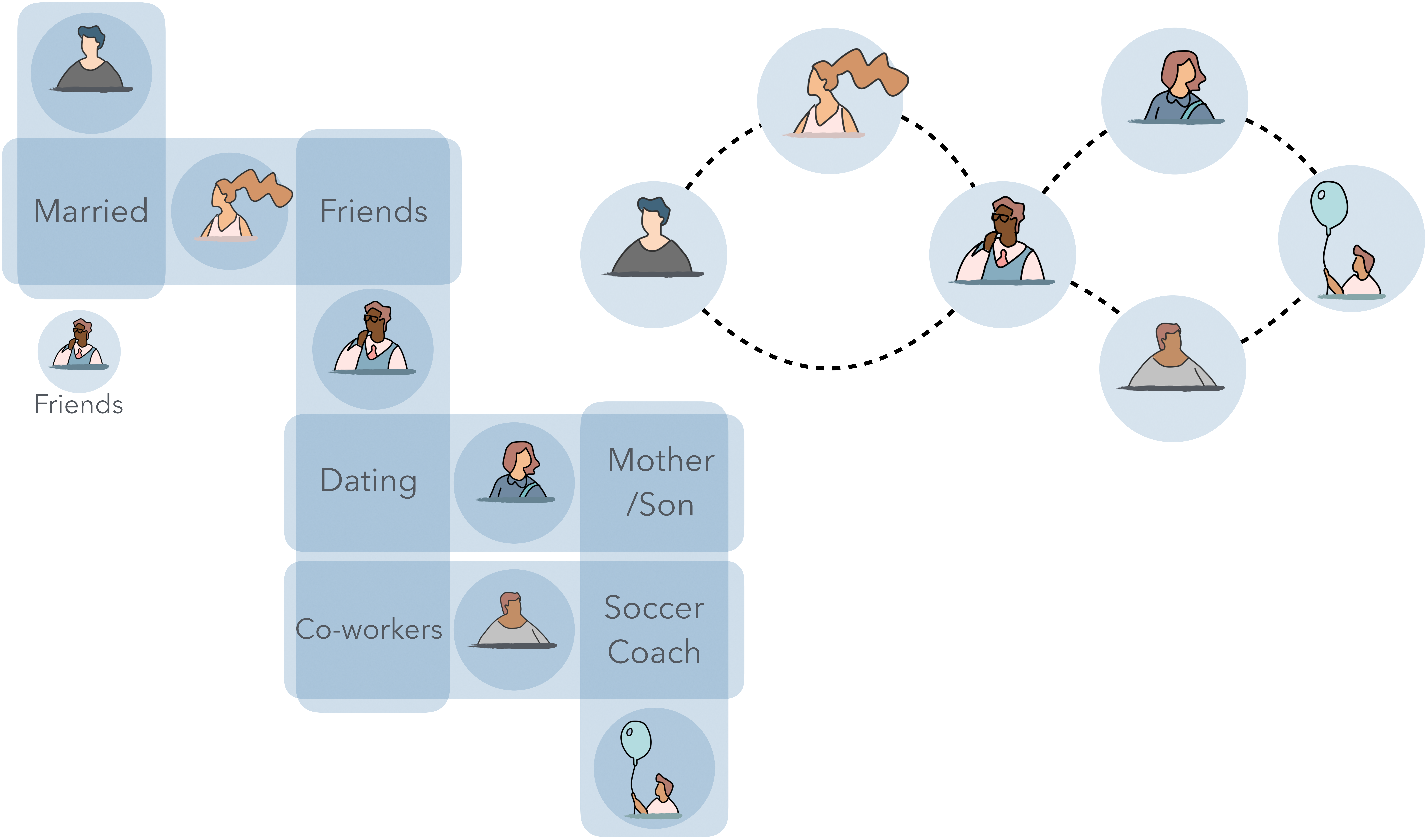

Married
Friends
Dating
Friends
Co-workers
Mother
/Son
Soccer
Coach
Layer 5

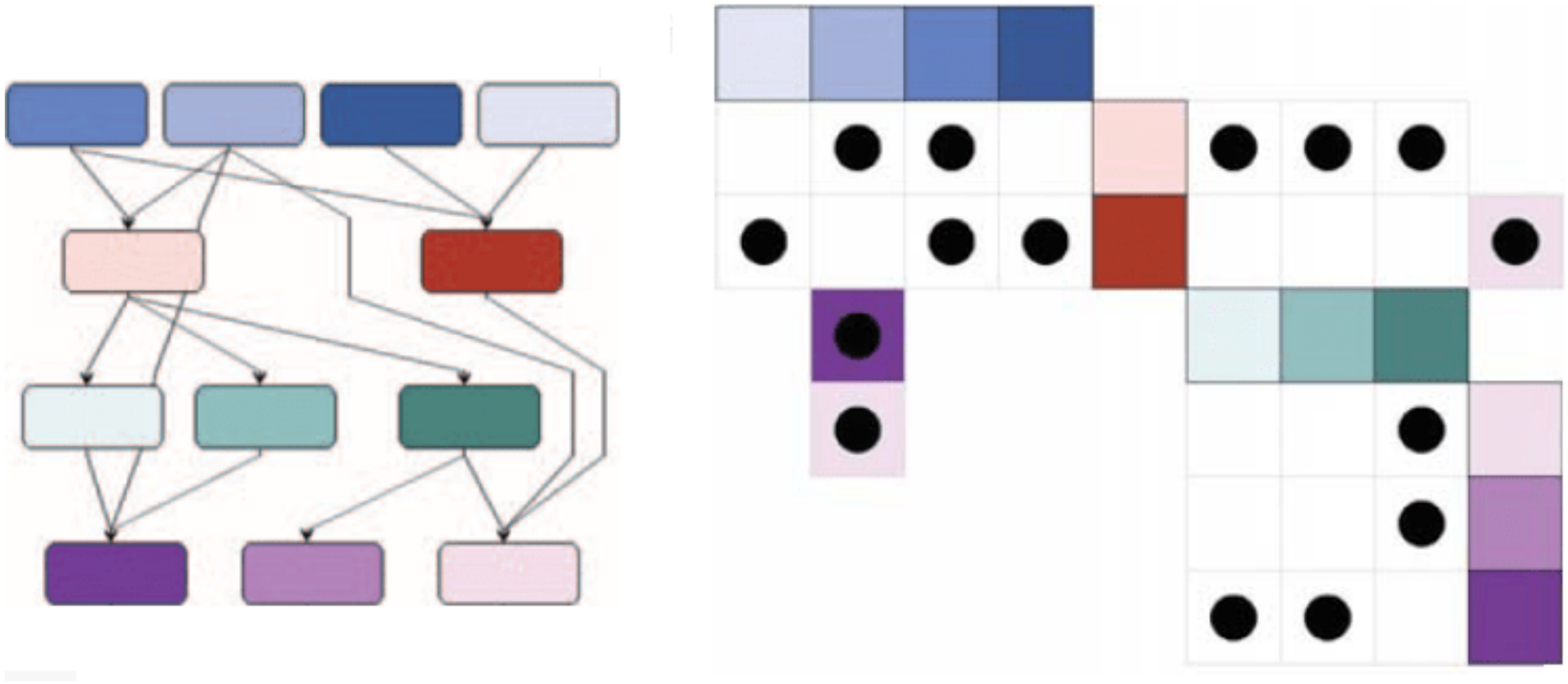

Married
Friends
Dating
Co-workers

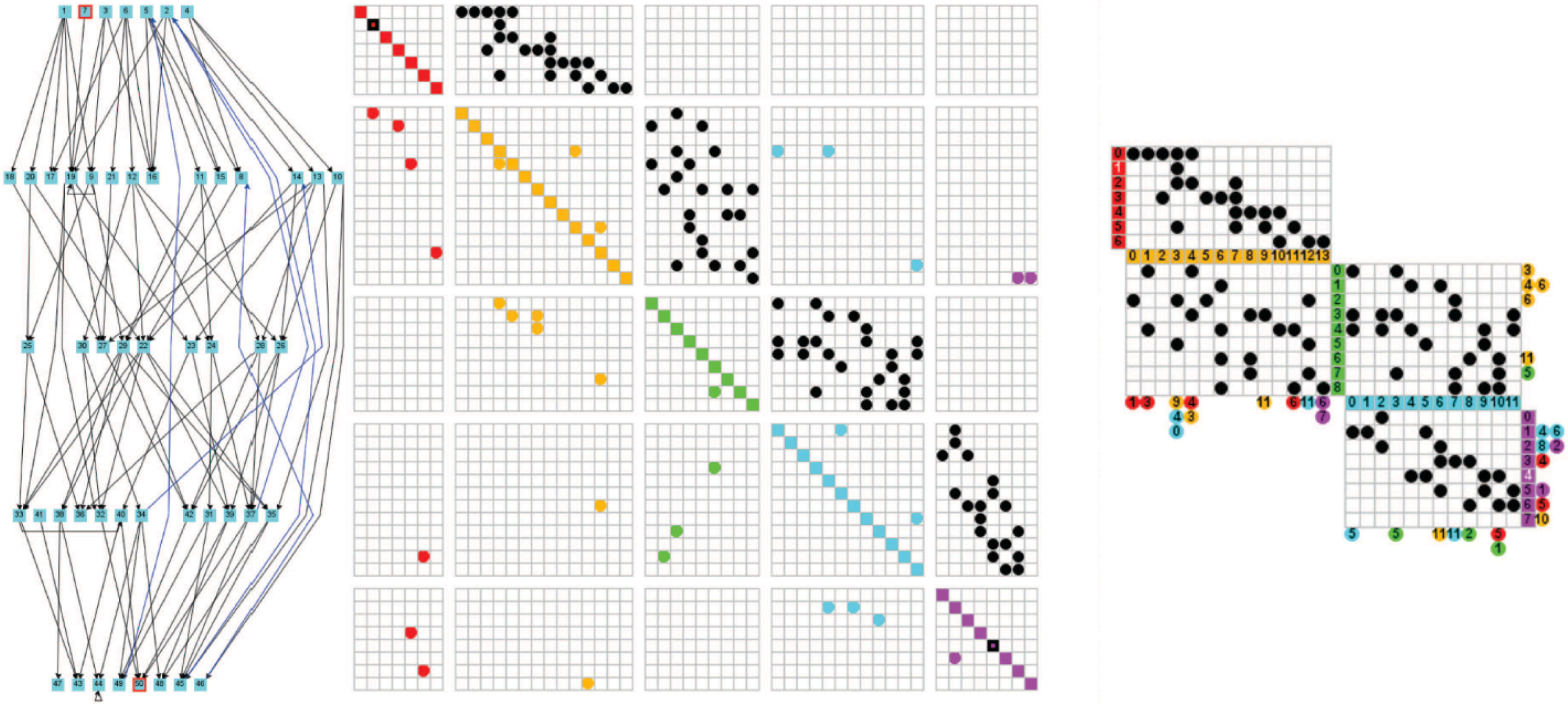

Friends
Mother
/Son
Soccer
Coach

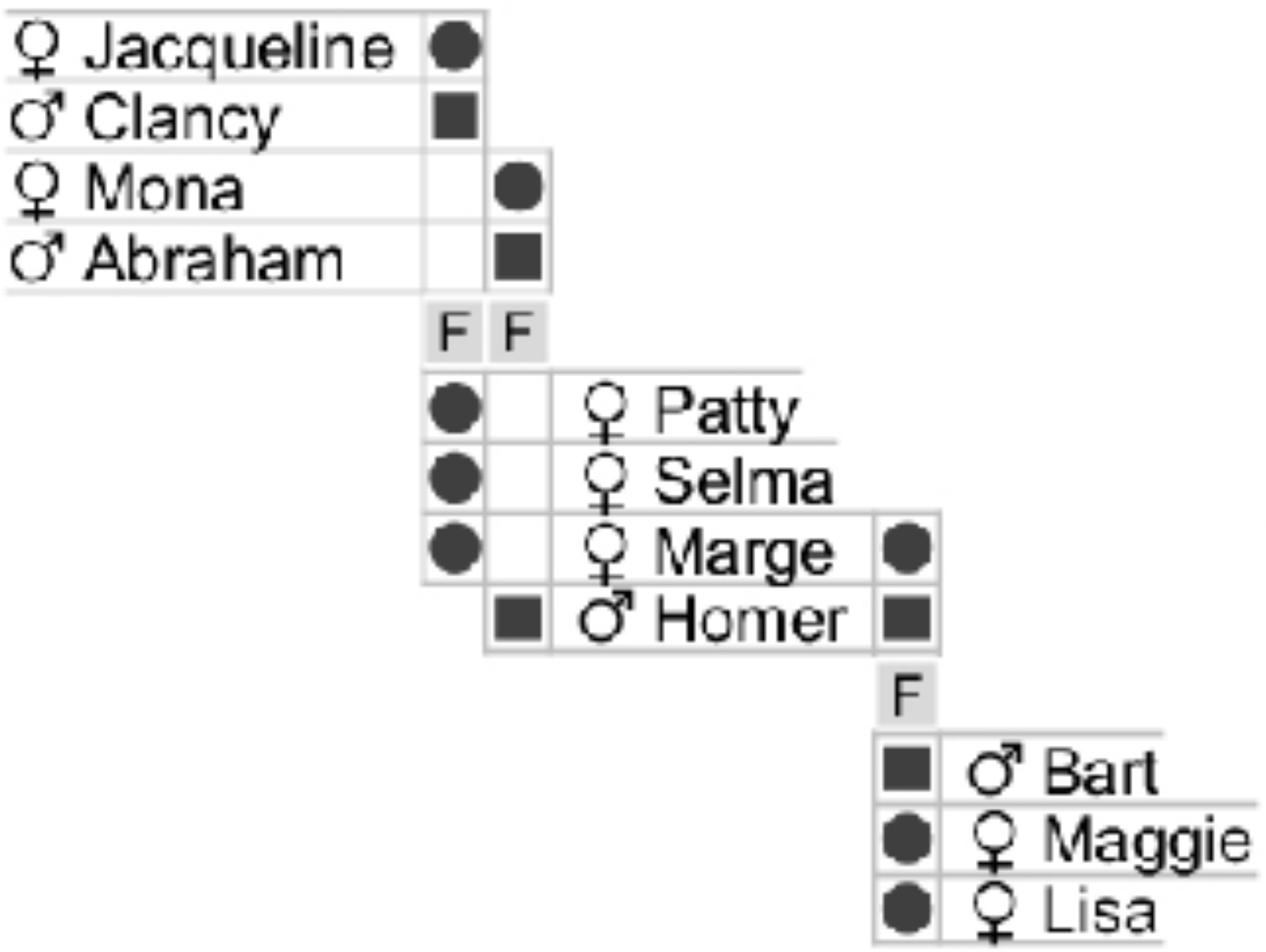
Layer 5

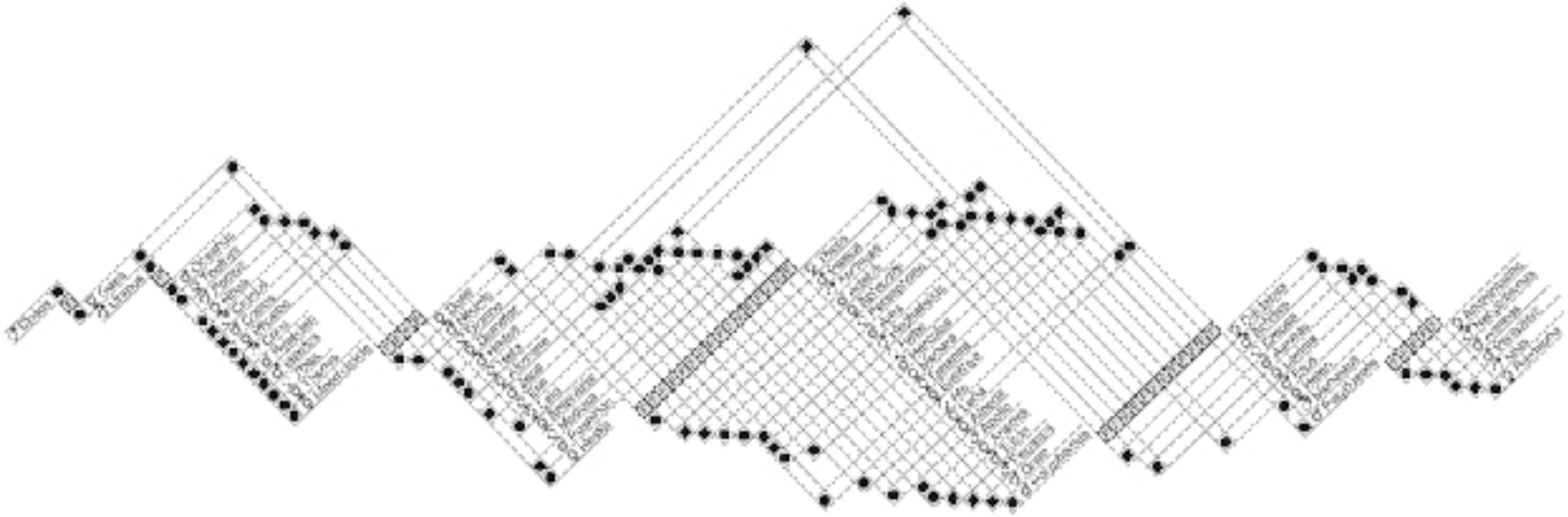

Married
Friends
Dating
Mother /Son
Co-workers
Soccer Coach
Friends


Married
Friends
Friends
Dating
Mother
/Son
Co-workers
Soccer
Coach






♀ Jacqueline
♂ Clancy
♀ Mona
♂ Abraham
F
F
♀ Patty
♀ Selma
♀ Marge
♂ Homer
F
♂ Bart
♀ Maggie
♀ Lisa

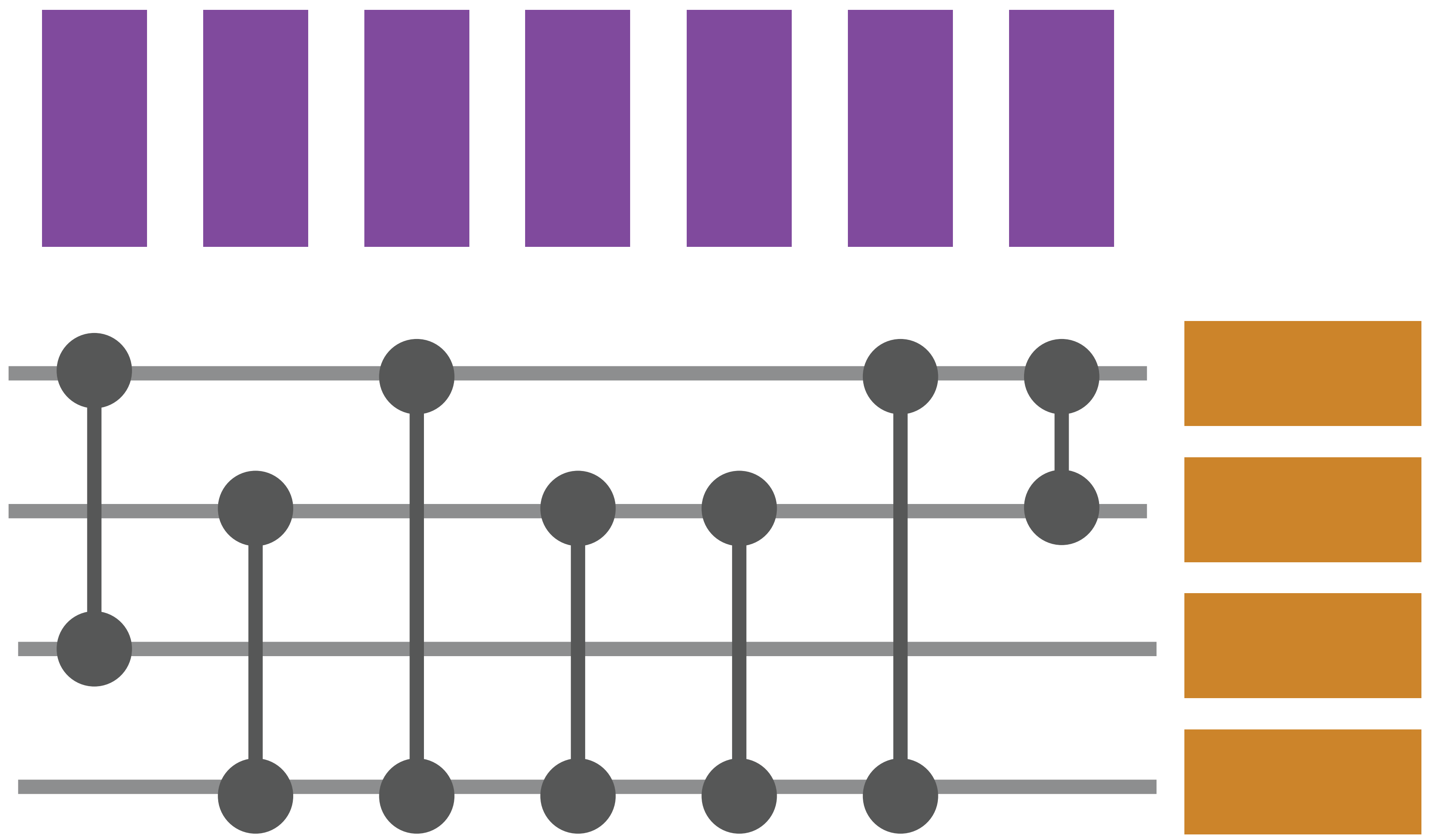


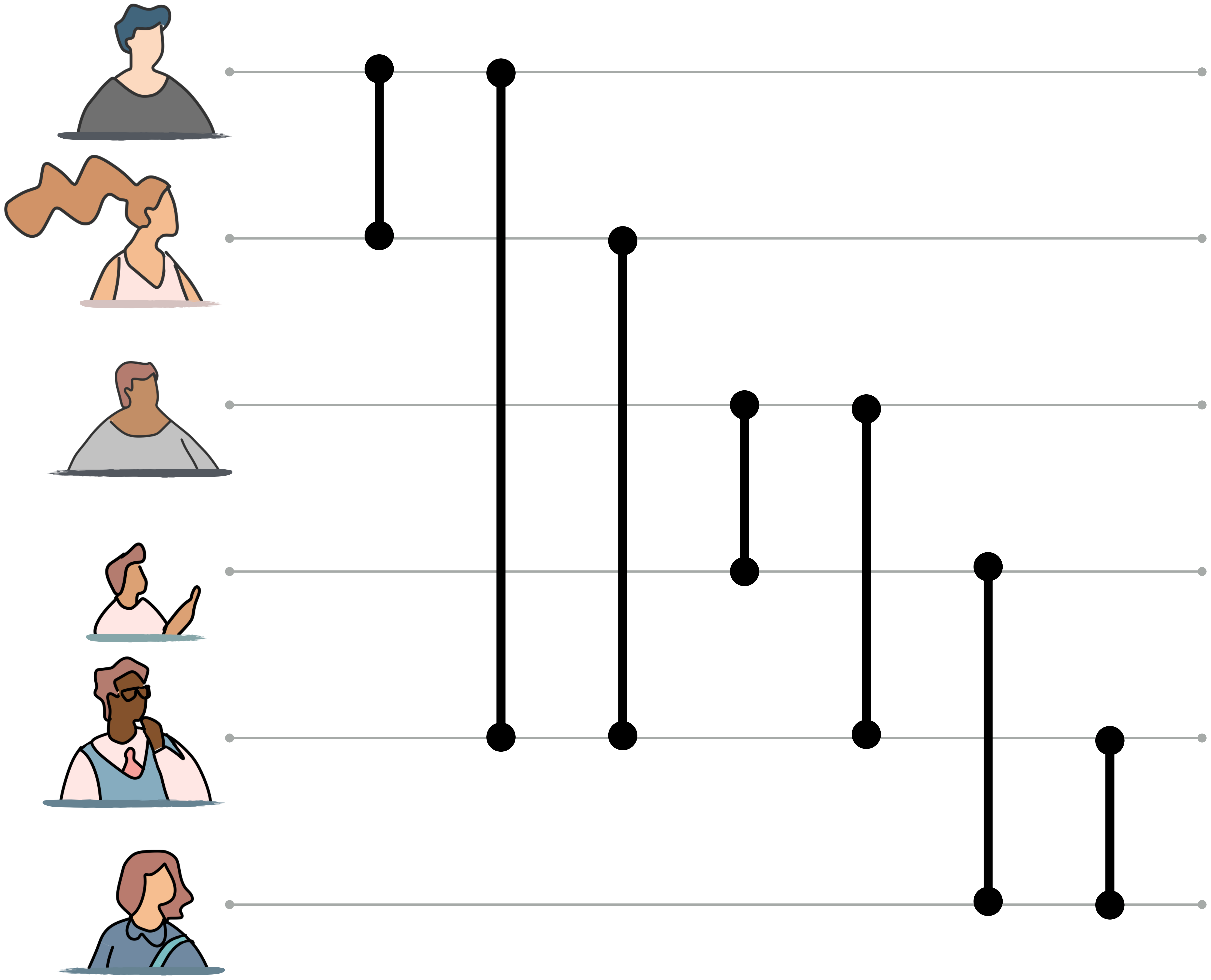
Well suited for layered networks

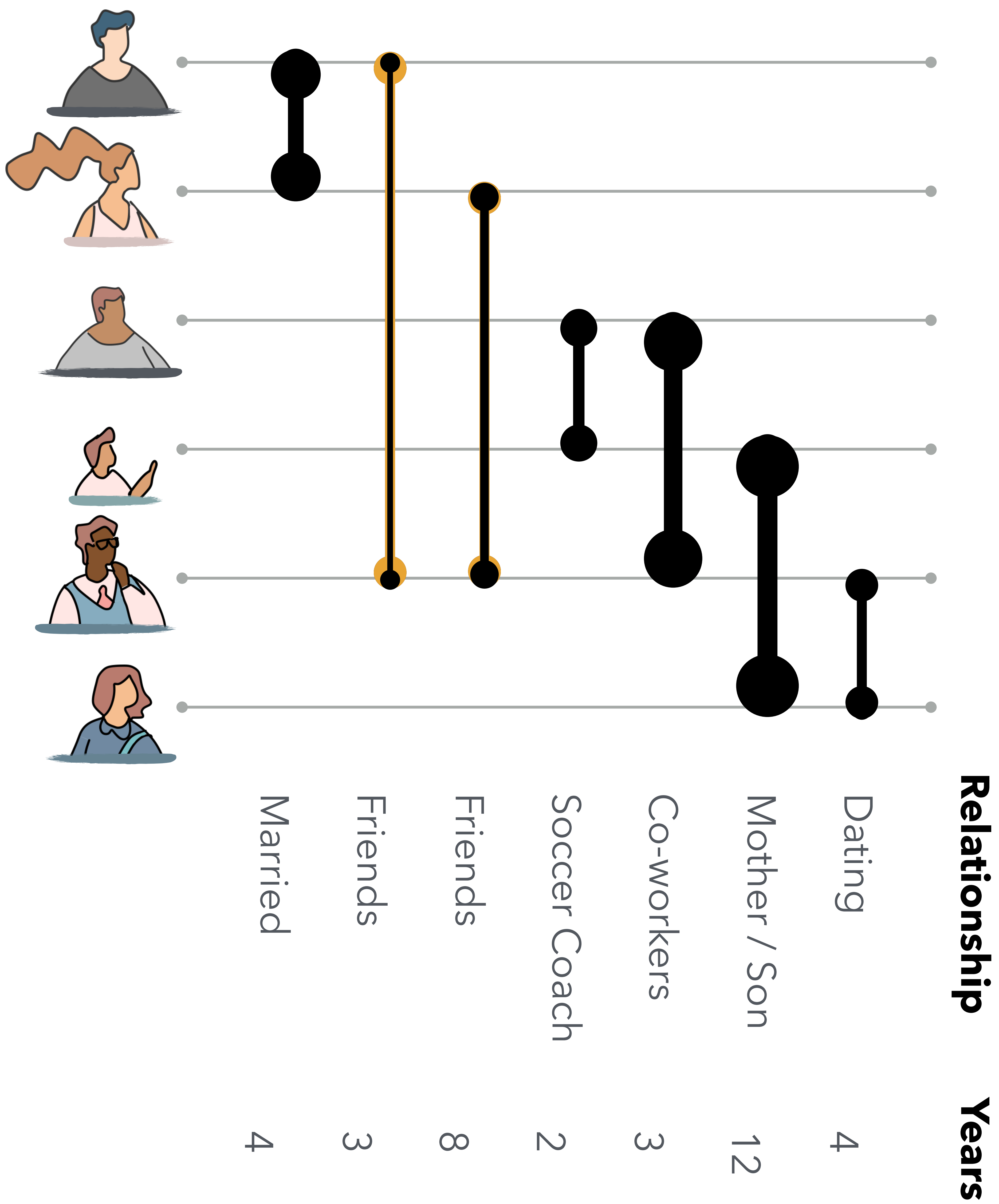
Links between nonconsecutive layers can be problematic to integrate and non-intuitive

Recommended for layered or k-partite networks with limited skiplinks.

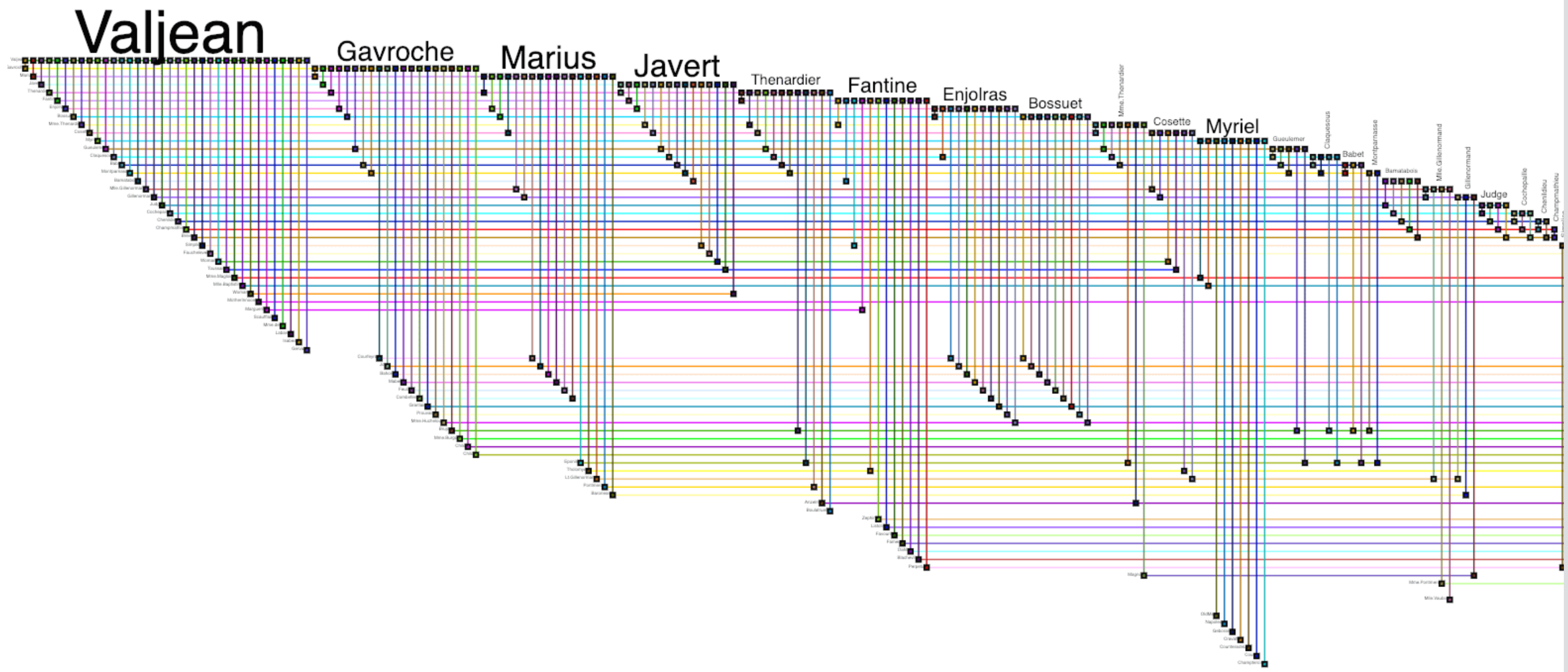
BioFabric



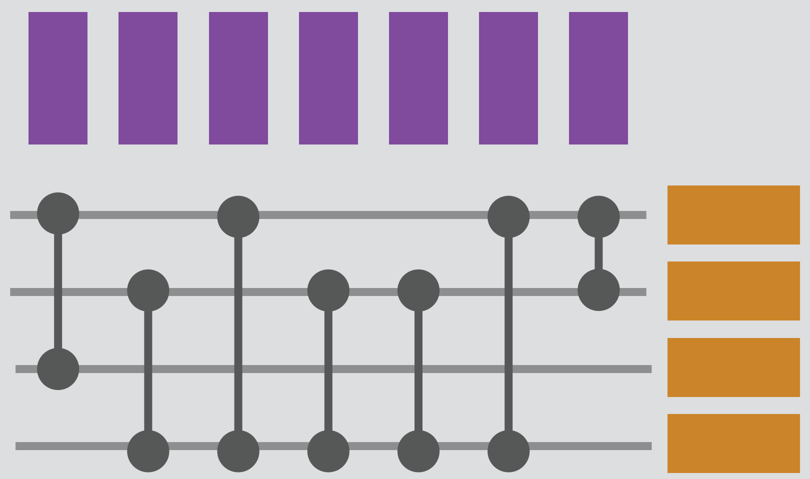




Name	Beverage	Day 1
Mark	Beer	1
Sue	Coke	0
Cole	Port	4
Jon	Coke	5
Tom	Beer	2
Abby	Port	3



Longabaugh, 2012

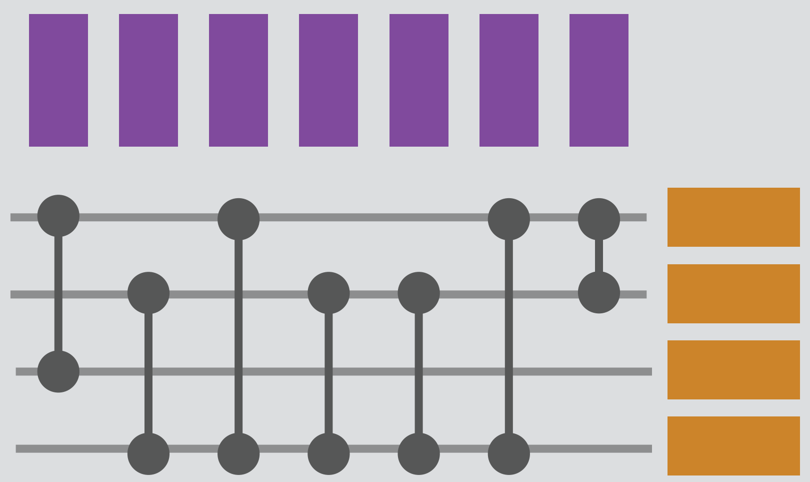


BioFabric

BioFabric

Can be used to visualize rich edge attributes and node attributes at the same time

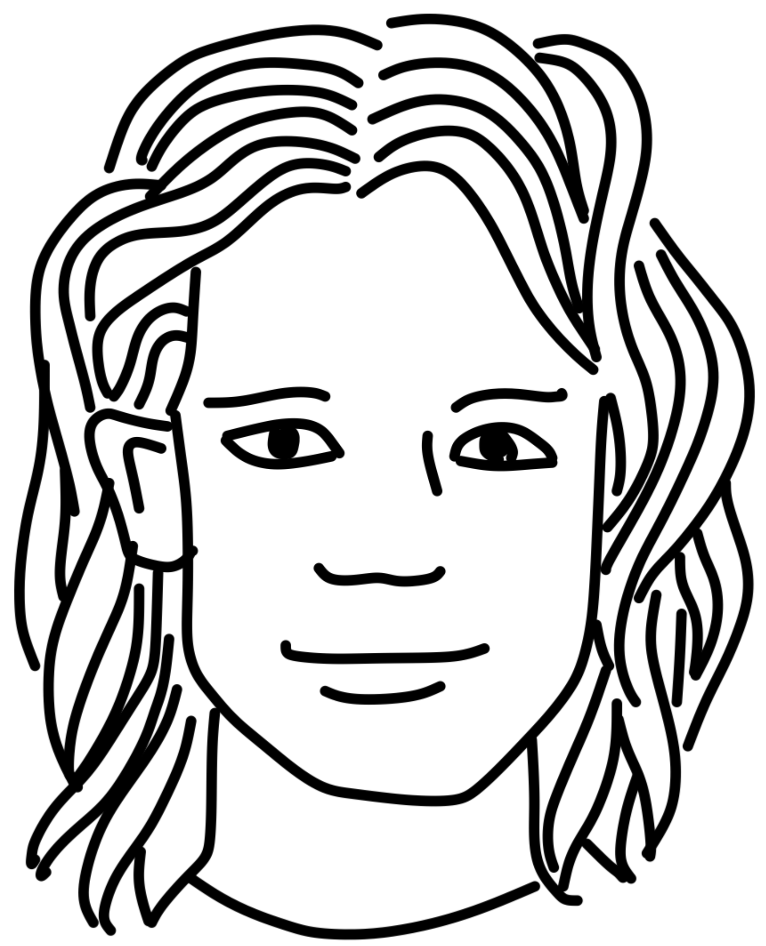
More difficult to discover neighbors and clusters in Biofabric compared to matrices.



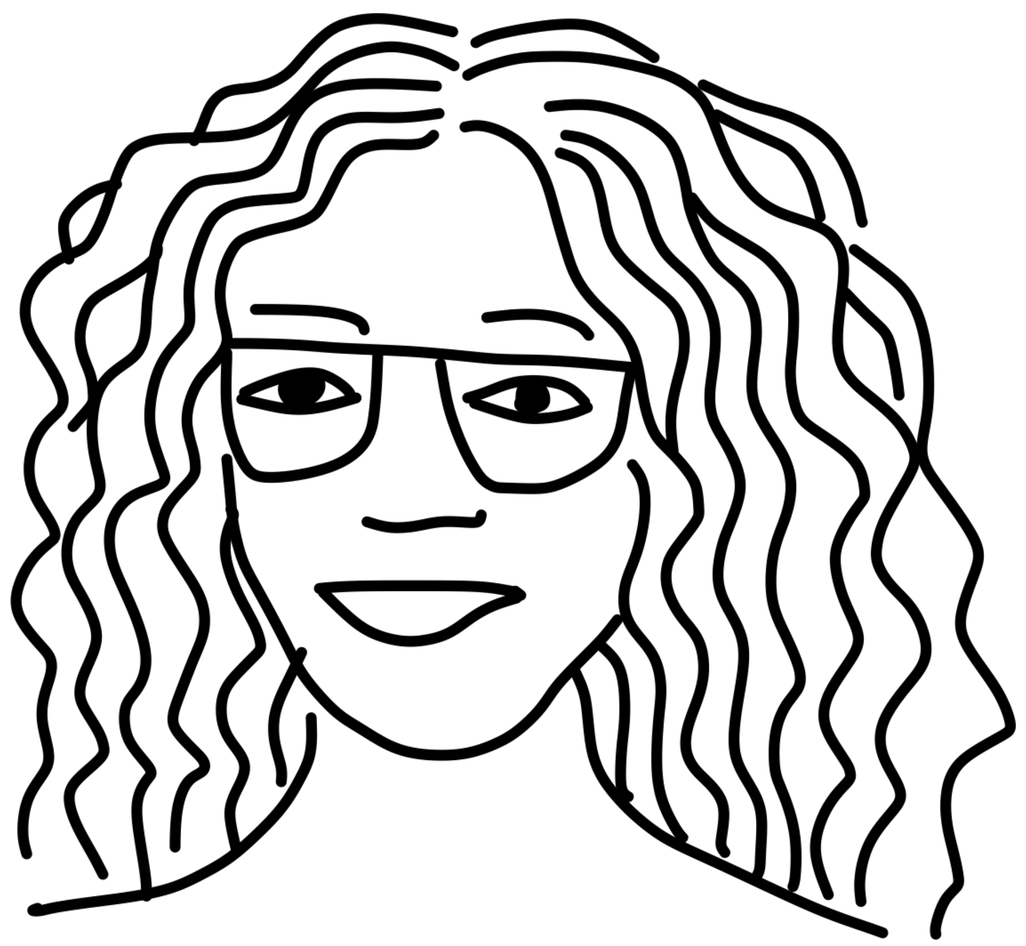
BioFabric

Recommended for small, sparse networks with many nodes and rich edge attributes

Tools and Applications

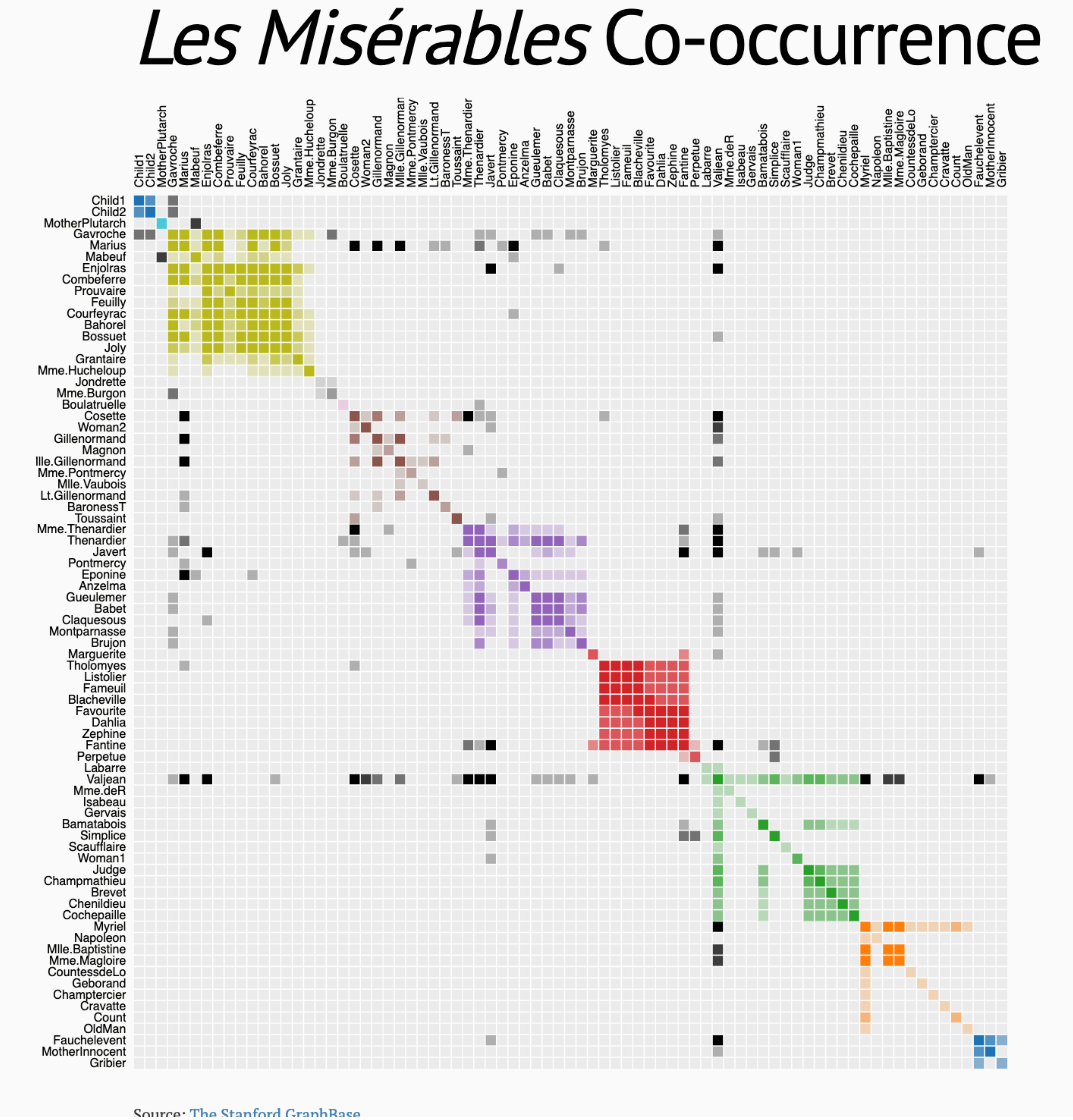


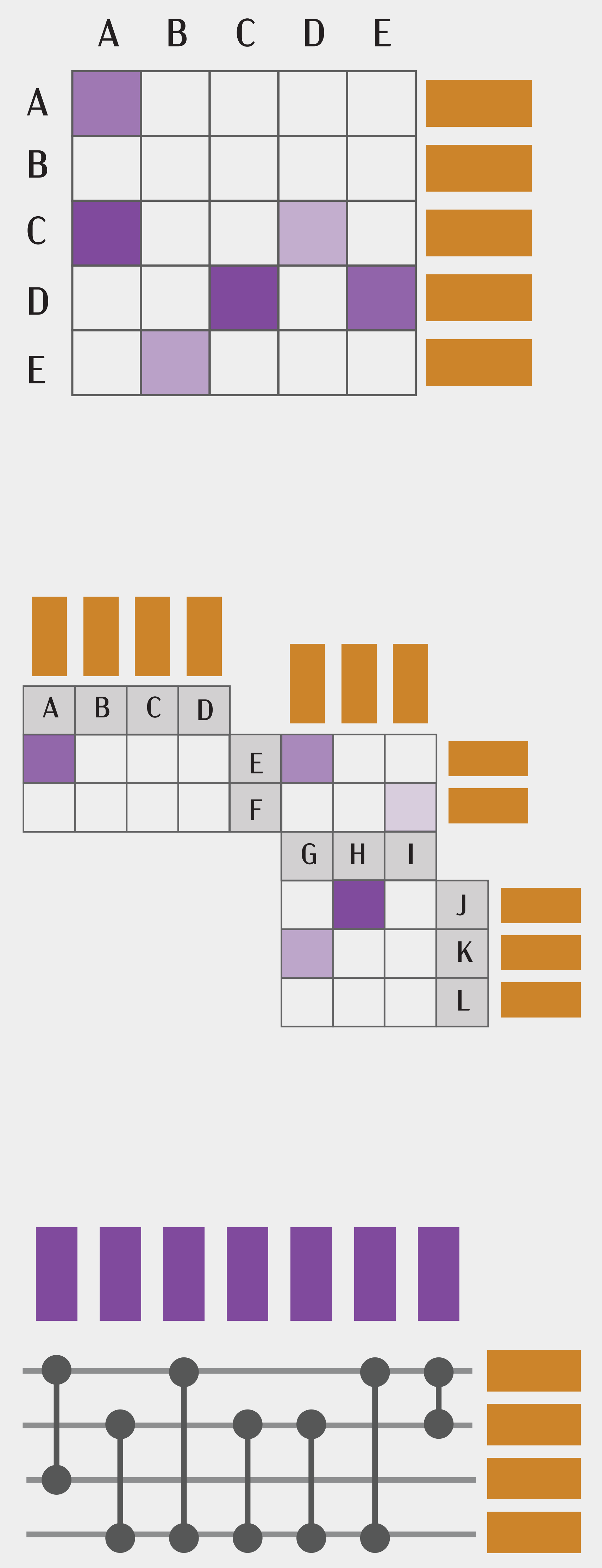
Brad
graphic designer

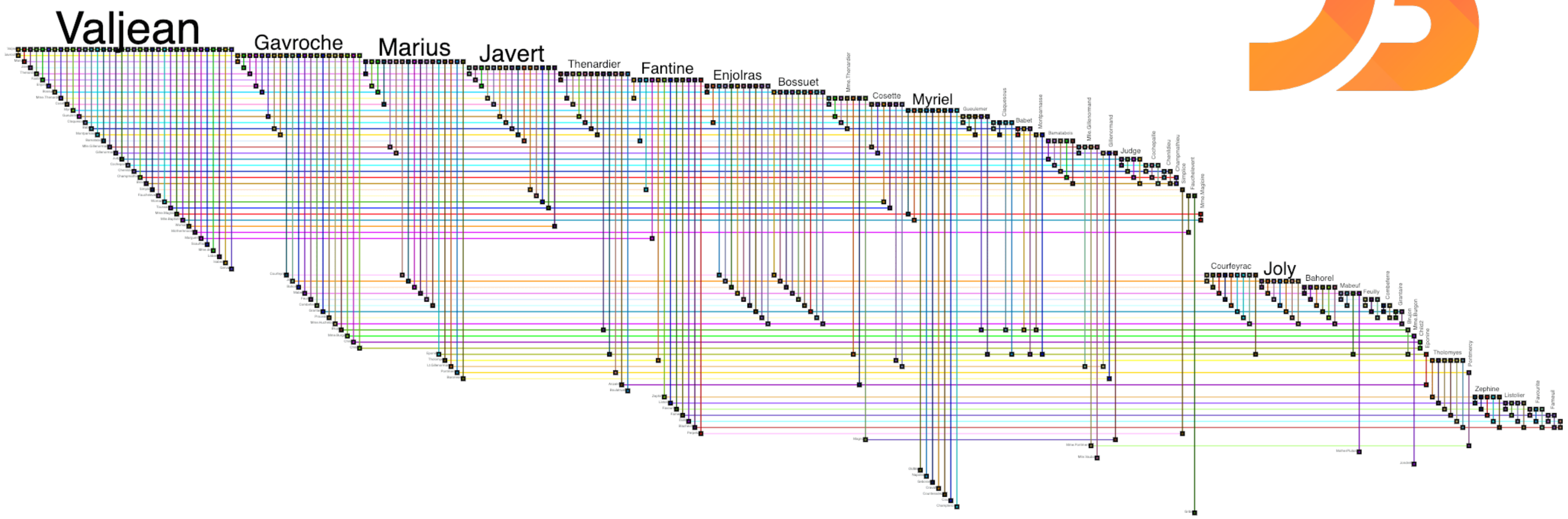


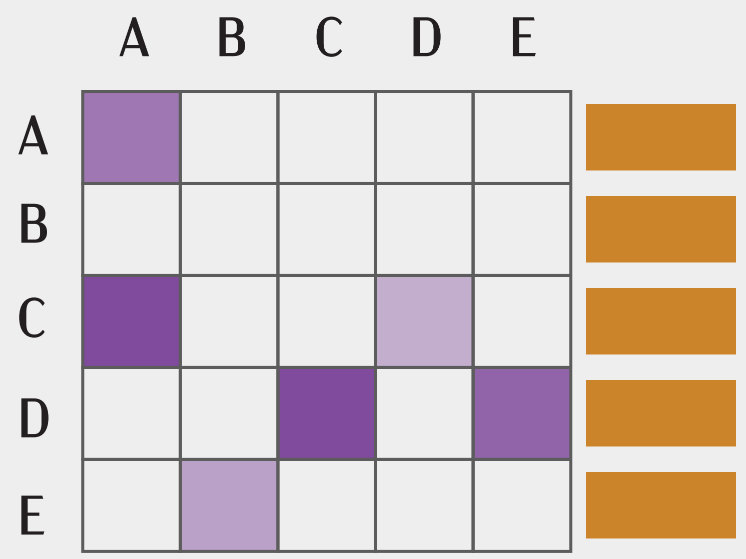
Maya
developer

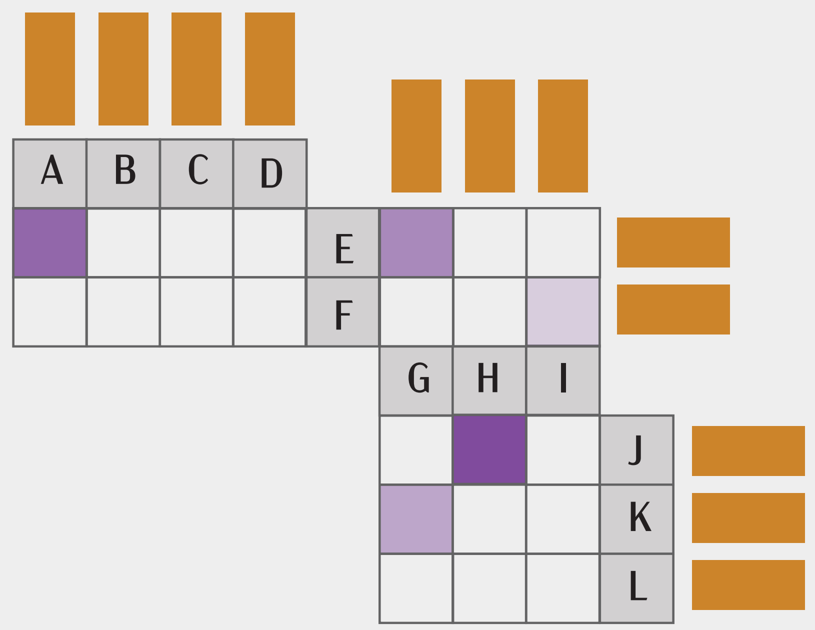

developer

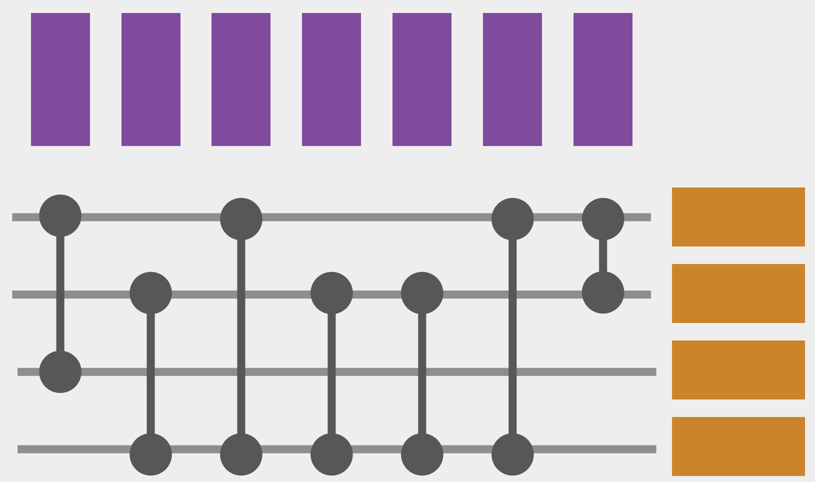

Les Misérables Co-occurrence
Child1
Child2
MotherPlutarch
Gavroche
Marius
Mabeuf
Enjolras
Combeferre
Prouvaire
Feuilly
Courfeyrac
Bahorel
Bossuet
Joly
Grantaire
Mme.Hucheloup
Jondrette
Mme.Burgon
Boulatruelle
Cosette
Woman2
Gillenormand
Magnon
Mlle.Gillenormand
Mme.Pontmercy
Mlle.Vaubois
Lt.Gillenormand
BaronessT
Toussaint
Mme.Thenardier
Thenardier
Javert
Pontmercy
Eponine
Anzelma
Gueulemer
Babet
Claquesous
Montparnasse
Brujon
Marguerite
Tholomyes
Listolier
Fameuil
Blacheville
Favourite
Dahlia
Zephine
Fantine
Perpetue
Labarre
Valjean
Mme.deR
Isabeau
Gervais
Bamatabois
Simplice
Scaufflaire
Woman1
Judge
Champmathieu
Brevet
Chenildieu
Cochepaille
Myriel
Napoleon
Mlle.Baptistine
Mme.Magloire
CountessdeLo
Geborand
Champtercier
Cravatte
Count
OldMan
Fauchelevent
MotherInnocent
Gribier
Source: The Stanford GraphBase


A B C D E
A
B
C
D
E
A B C D
E
F
G H I
J
K
L

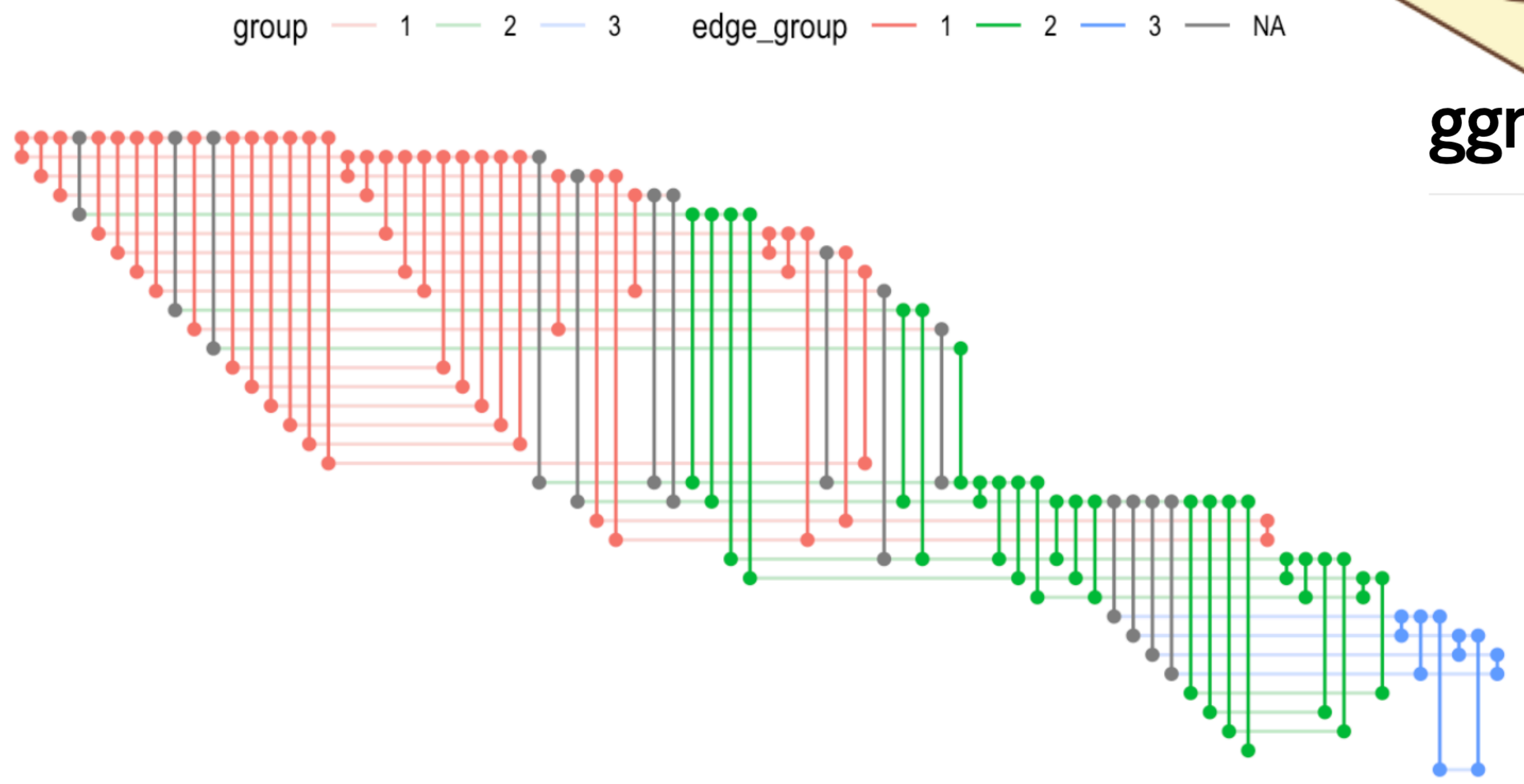


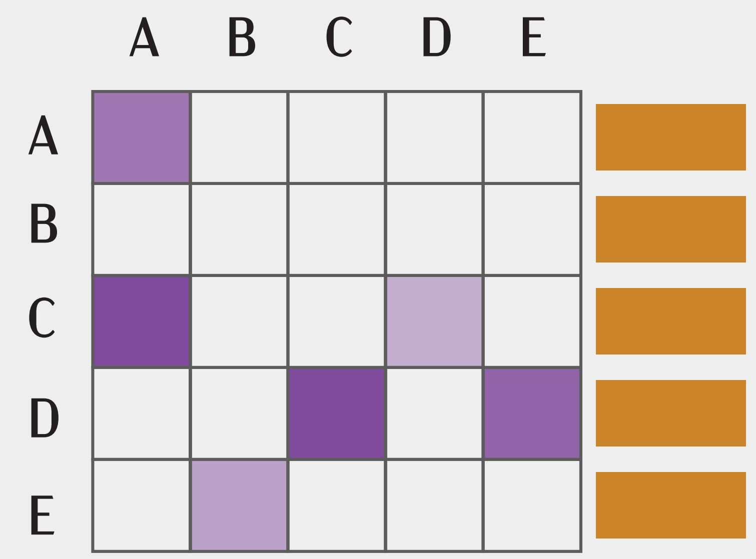


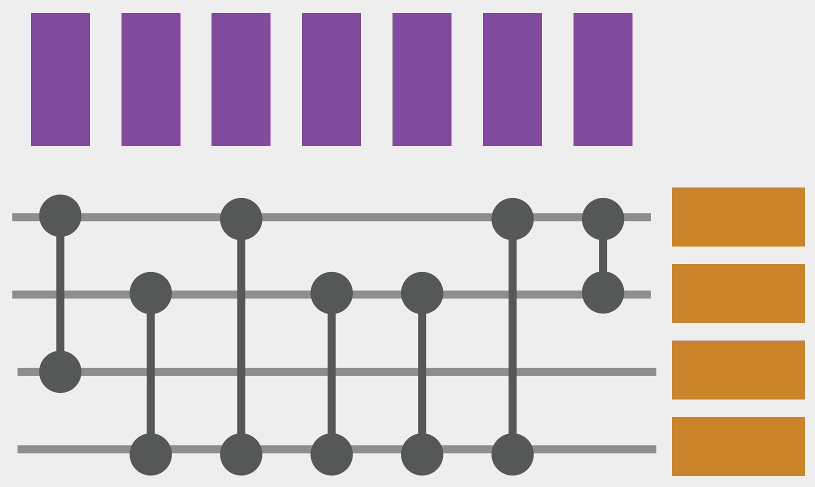




http://www.biofabric.org

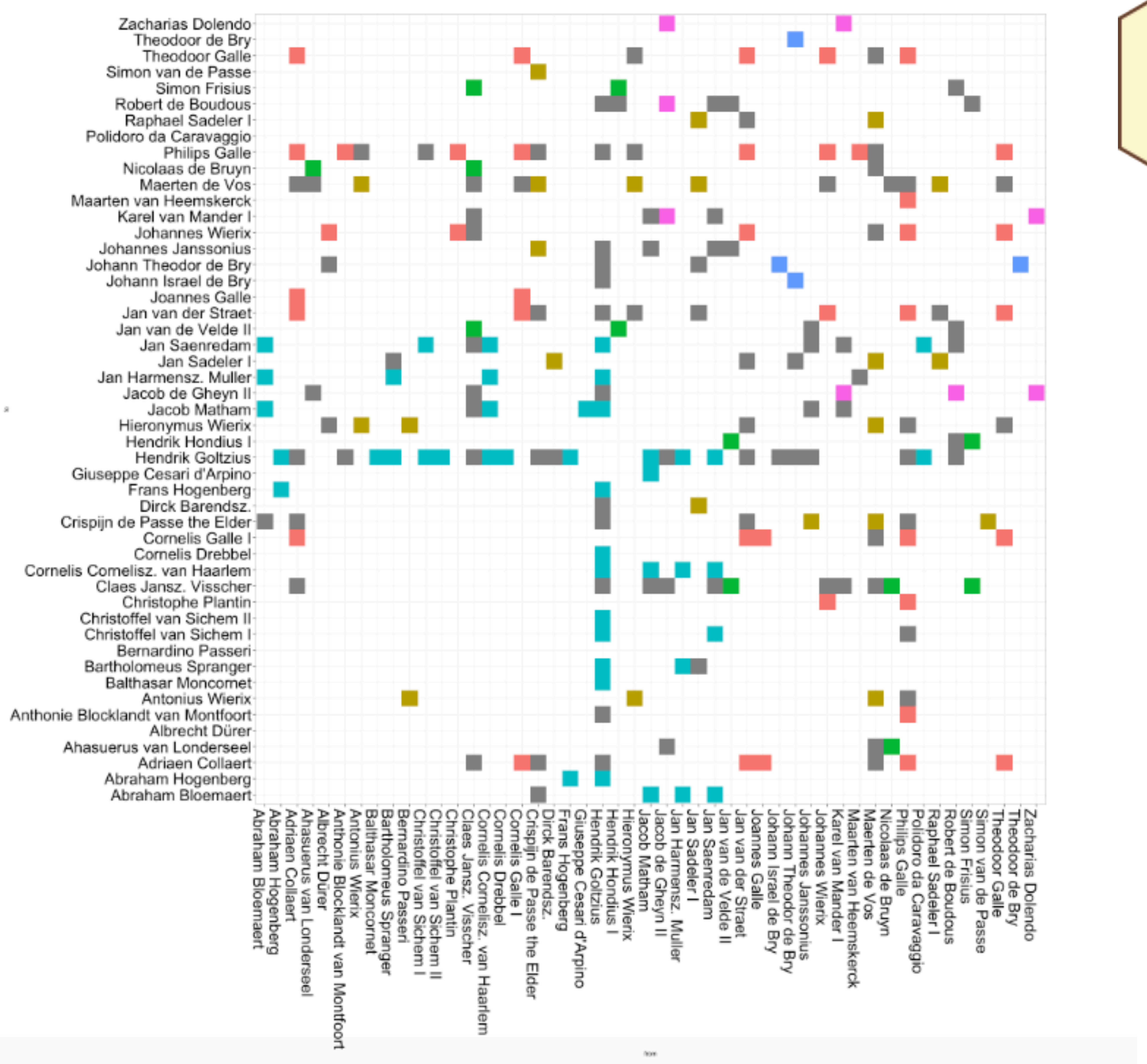




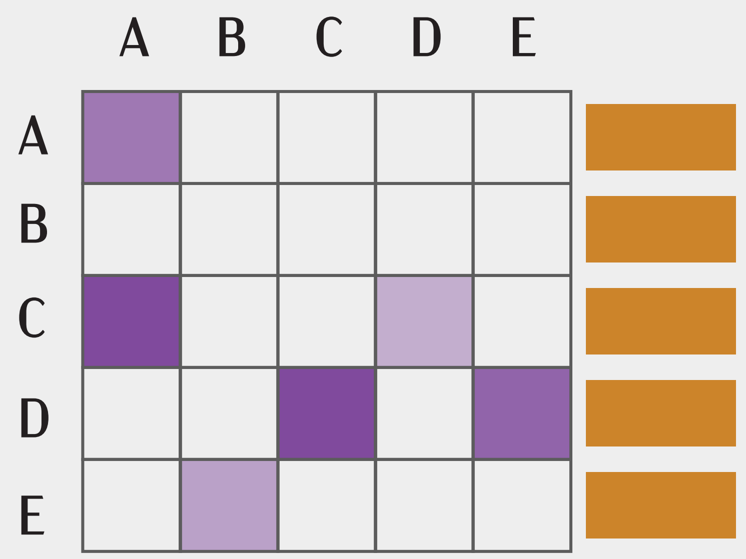


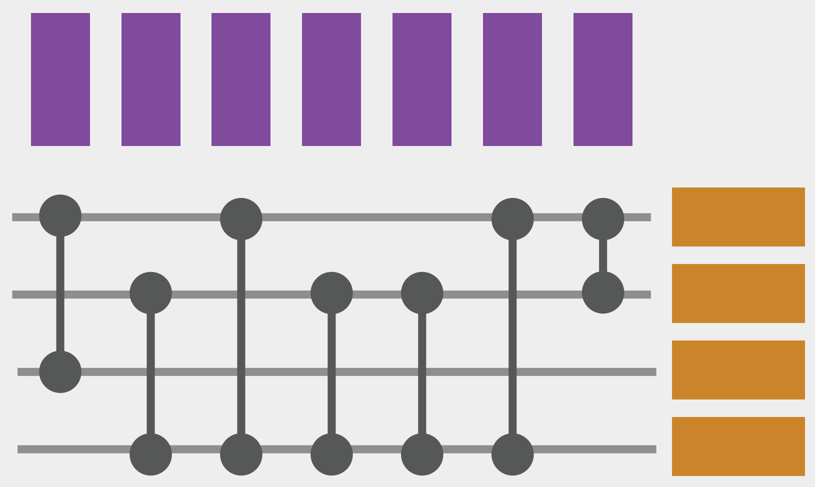
http://www.biofabric.org


developer


Zacharias Dolendo
Theodoor de Bry
Theodoor Galle
Simon van de Passe
Simon Frisius
Robert de Boudous
Raphael Sadeler I
Polidoro da Caravaggio
Philips Galle
Nicolaas de Bruyn
Maerten de Vos
Maarten van Heemskerck
Karel van Mander I
Johannes Wierix
Johannes Janssonius
Johann Theodor de Bry
Johann Israel de Bry
Joannes Galle
Jan van der Straet
Jan van de Velde II
Jan Saenredam
Jan Sadeler I
Jan Harmensz. Muller
Jacob de Gheyn II
Jacob Matham
Hieronymus Wierix
Hendrik Hondius I
Hendrik Goltzius
Giuseppe Cesari d'Arpino
Frans Hogenberg
Dirck Barendsz.
Crispijn de Passe the Elder
Cornelis Galle I
Cornelis Drebbel
Cornelis Cornelisz. van Haarlem
Claes Jansz. Visscher
Christophe Plantin
Christoffel van Sichem II
Christoffel van Sichem I
Bernardino Passeri
Bartholomeus Spranger
Balthasar Moncornet
Antonius Wierix
Anthonie Blocklandt van Montfoort
Albrecht Dürer
Ahasuerus van Londerseel
Adriaen Collaert
Abraham Hogenberg
Abraham Bloemaert

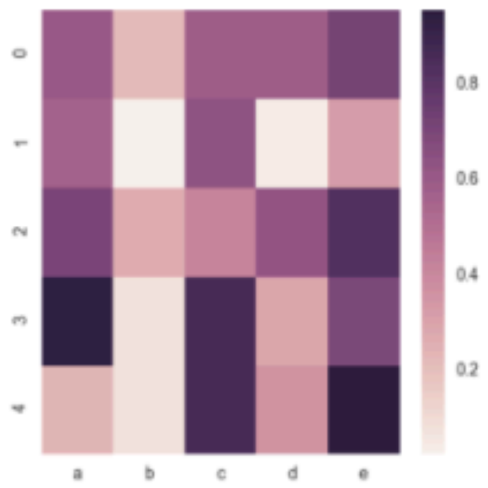
ggraph


A B C D E
A
B
C
D
E

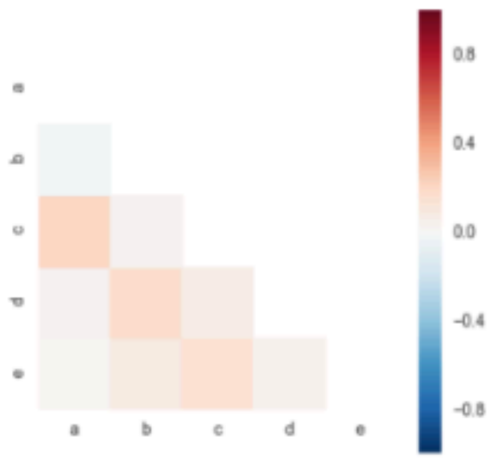


python

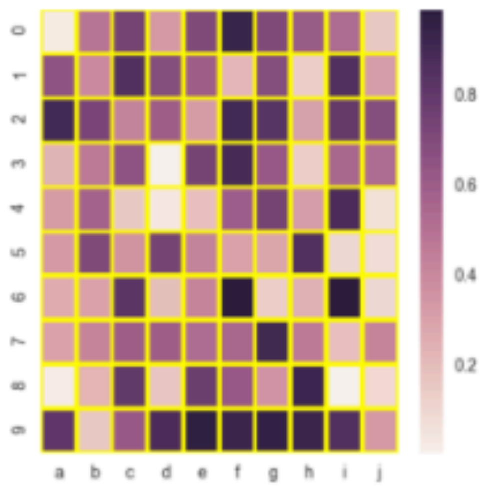
matplotlib



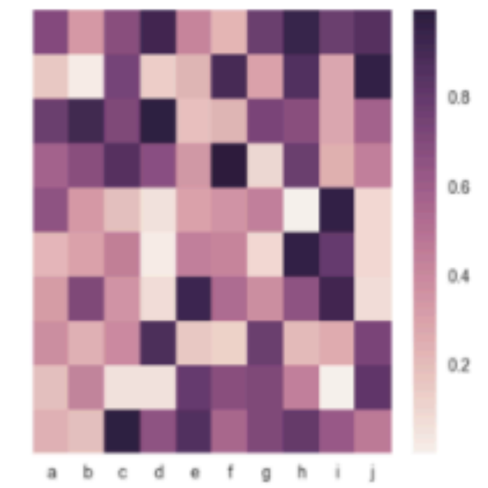
#90 Input format for heatmap



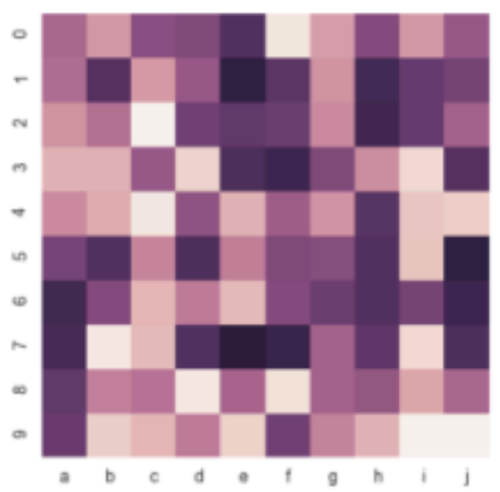
#90 Half heatmap



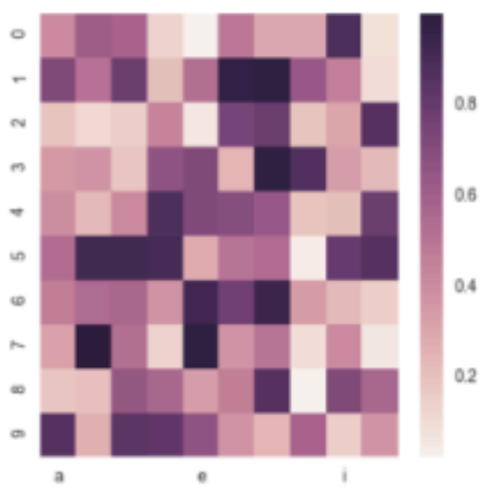
#91 Custom seaborn heatmap



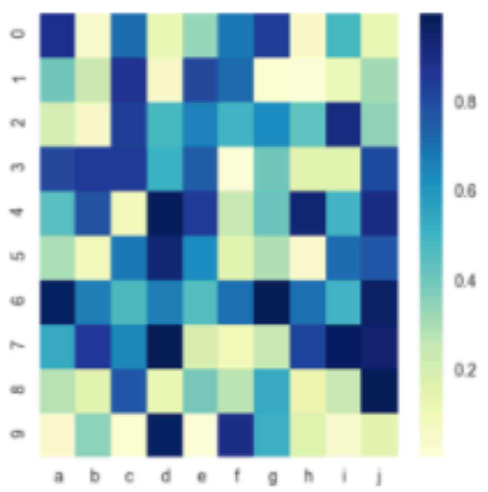
#91 Custom seaborn heatmap



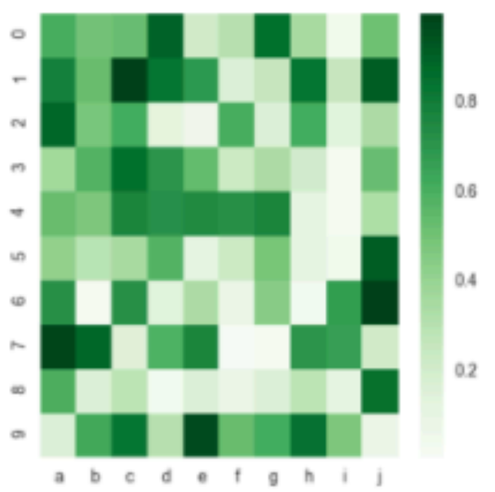
#91 Custom seaborn heatmap



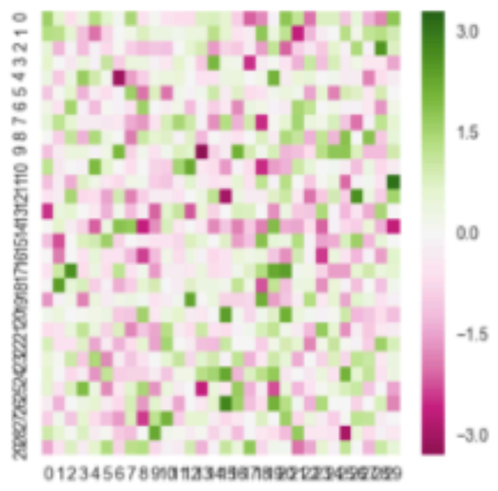
#91 Custom seaborn heatmap



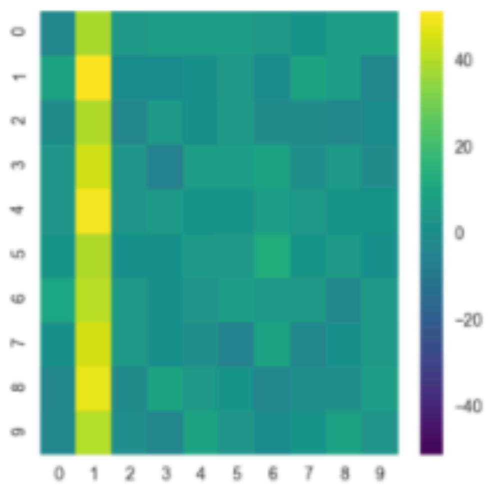
#92 Control heatmap color



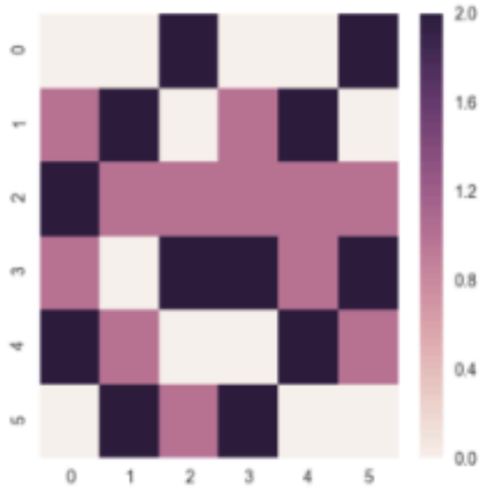
#92 Control heatmap color



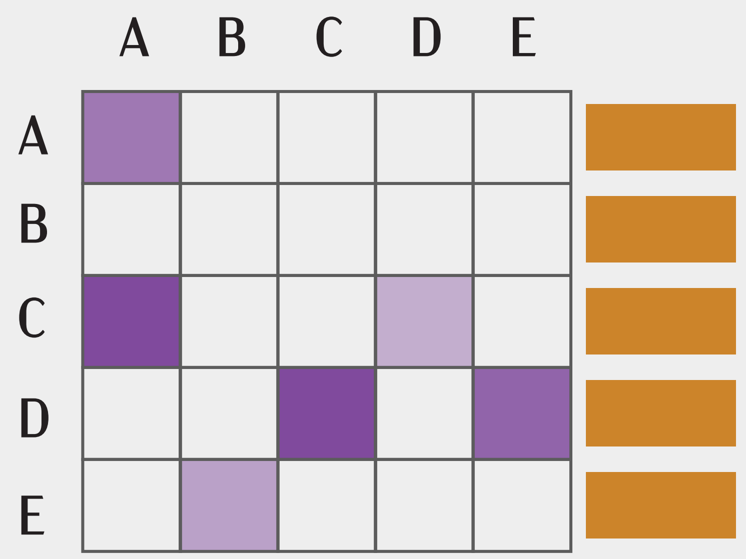
#92 Control heatmap color

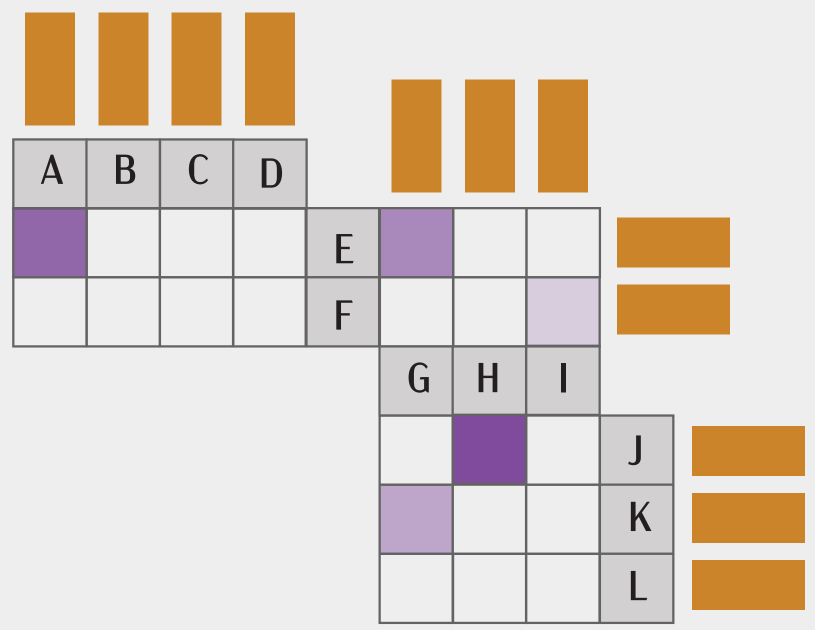


#94 Column normalization on heatmap



#92 Turn your data categorical for heatmap





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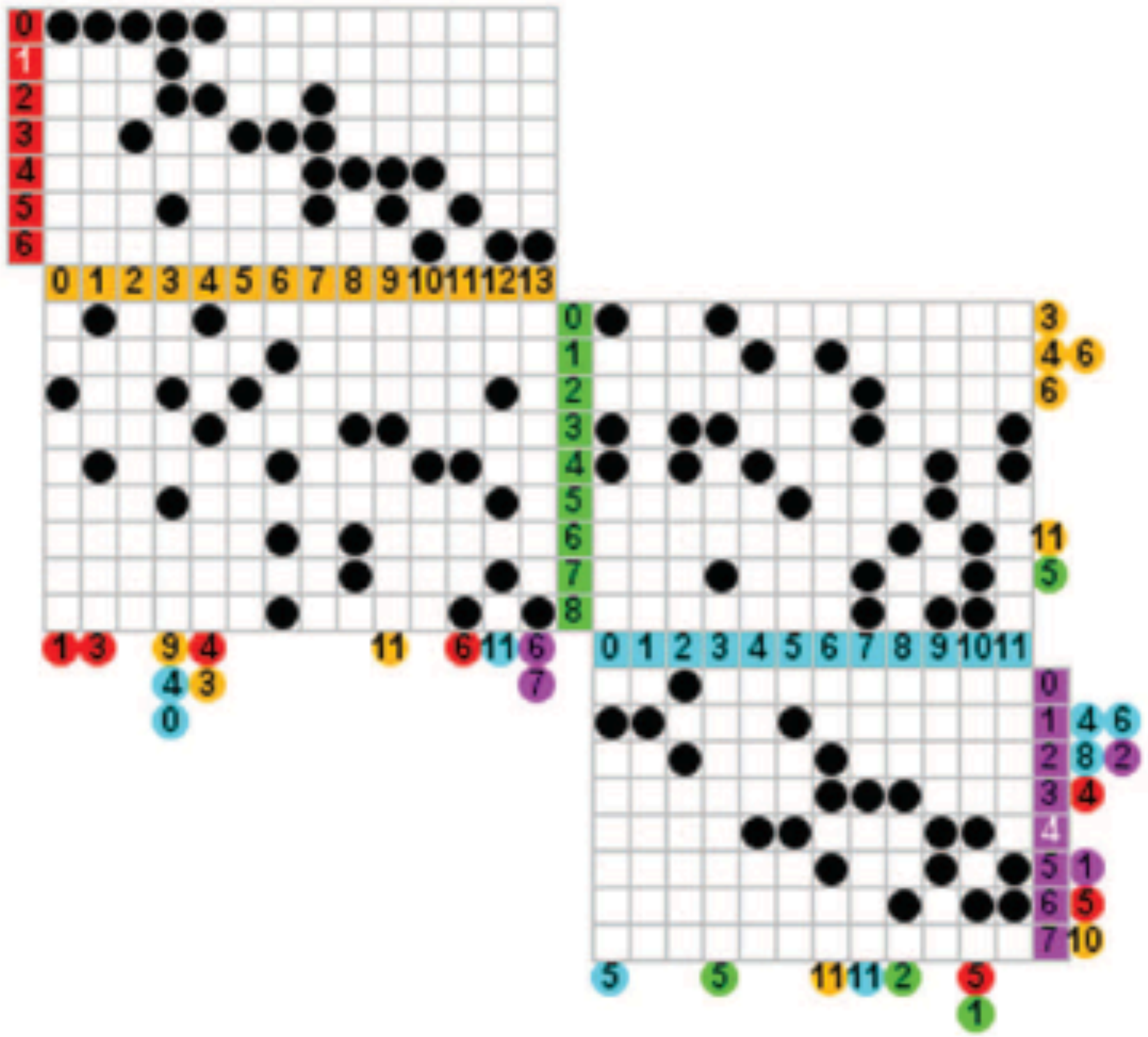
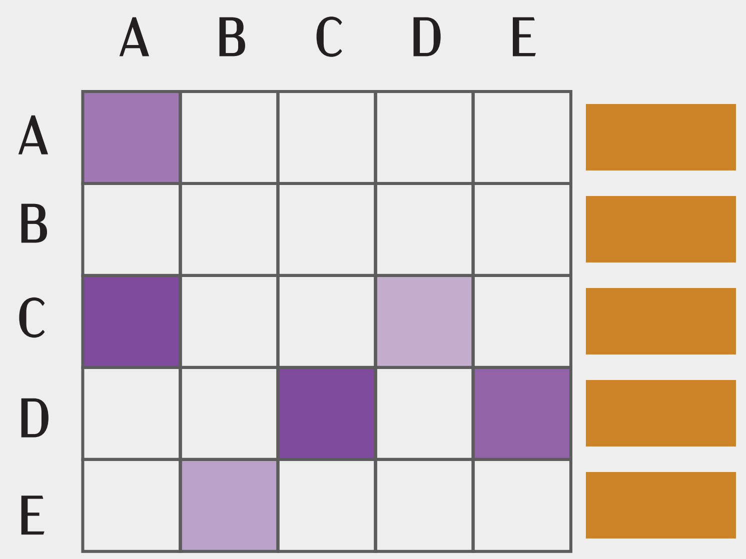
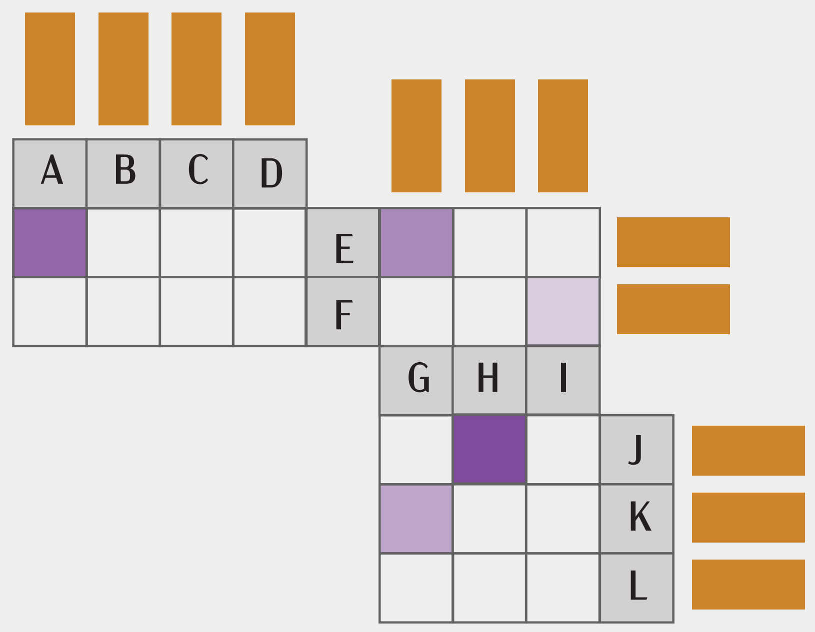
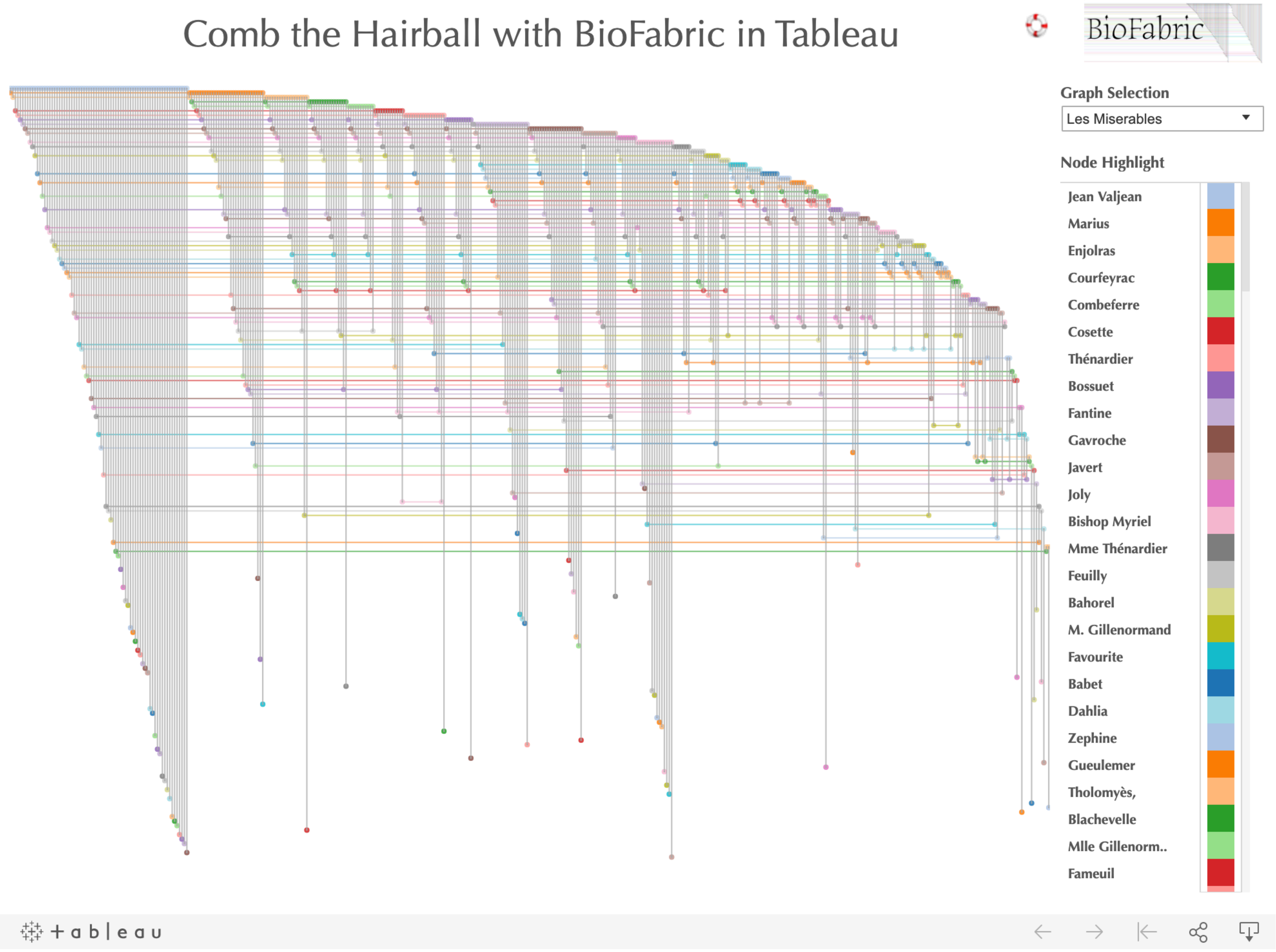


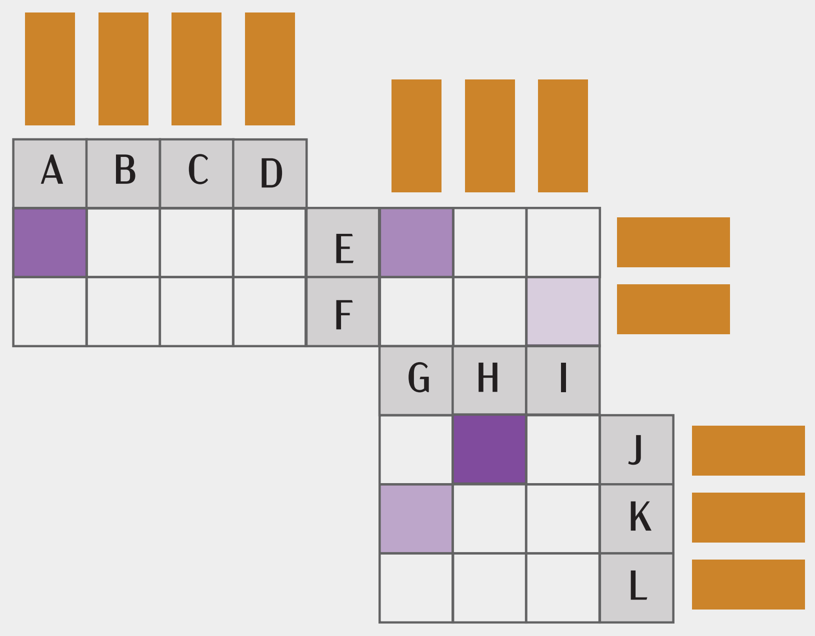


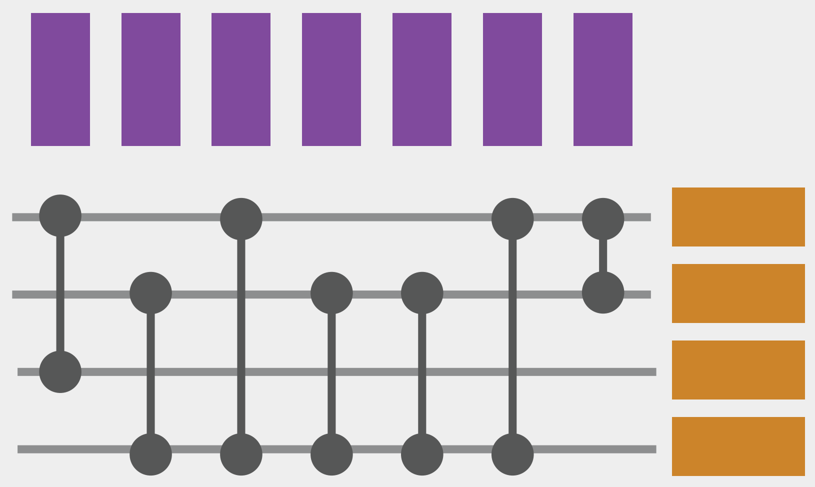


graphic
designer

Comb the Hairball with BioFabric in Tableau

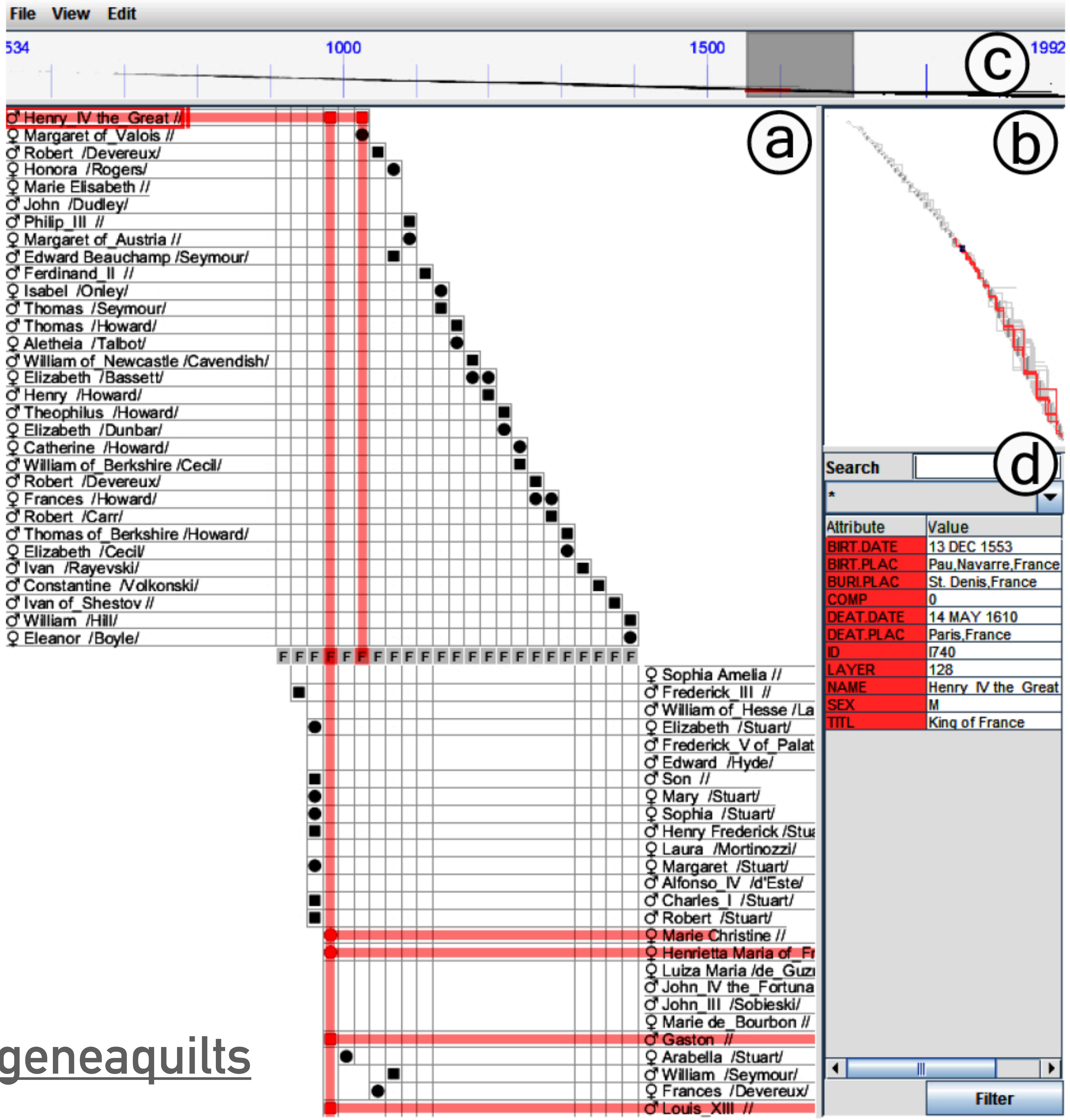




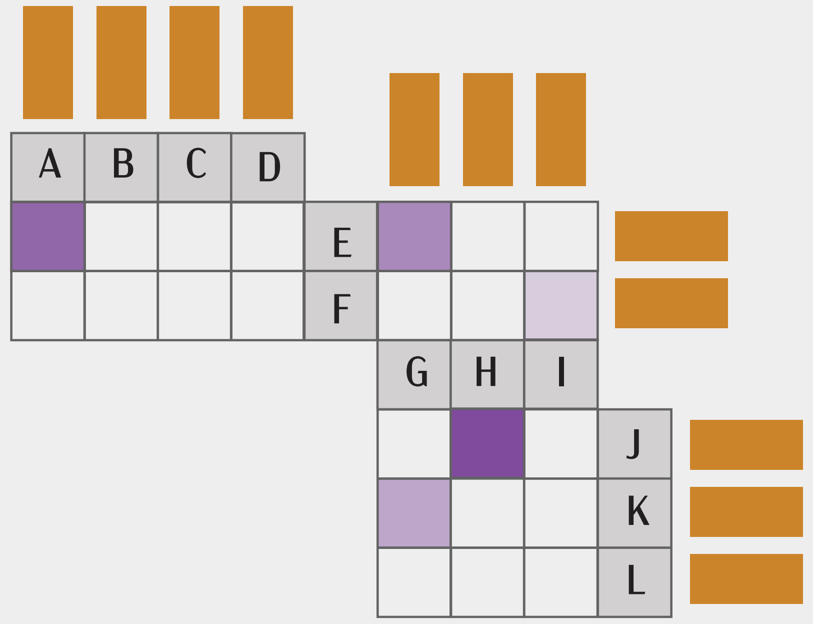


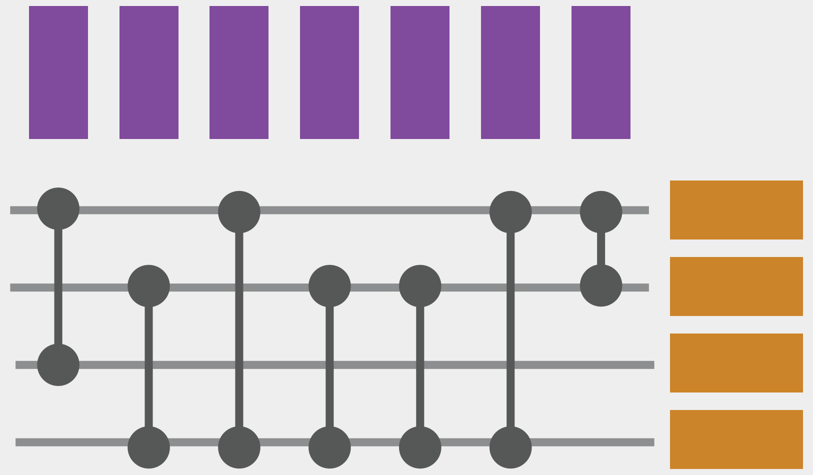
graphic designer

Genea Quilts

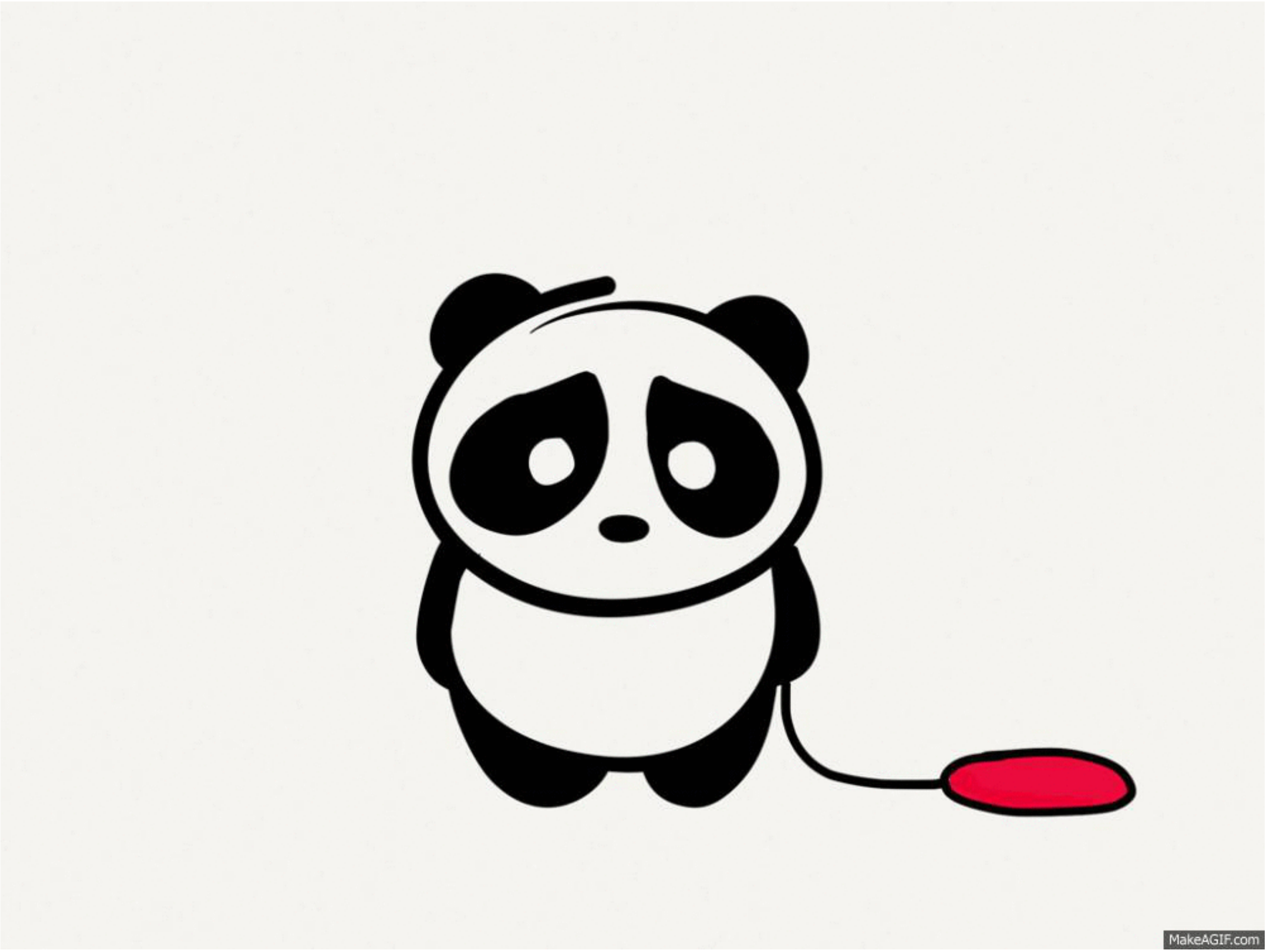


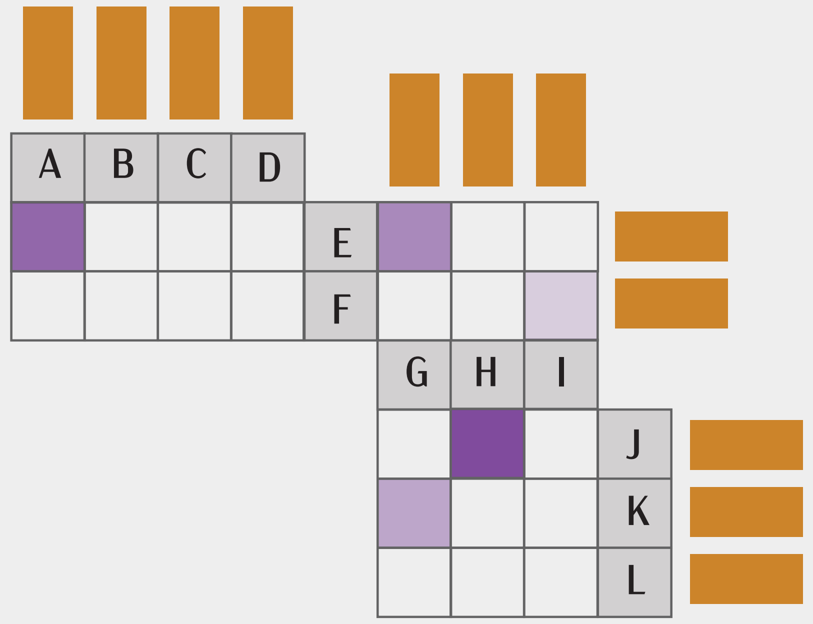
https://aviz.fr/geneaquilts

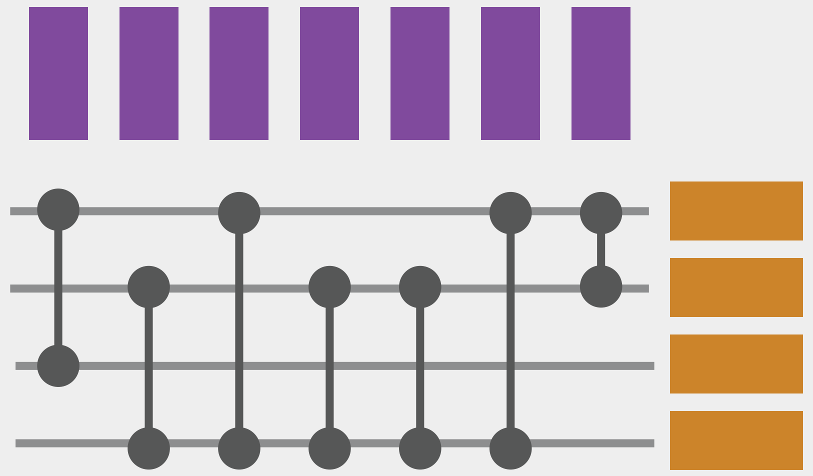




graphic
designer







Tabular Activity

Nodes

	Name	#Tweets	Following	Account Type
1	Michelle Obama	1,178	18	Person
2	Tina Tchen	428	173	Person
3	Time's Up	3,092	634	Organization
4	NowThis	*13,530*	*1,216*	Organization
5	Kerry Washington	*3,011*	676	Person
6	MeToo	330	337	Organization
7	Monica Ramirez	7,839	1,248	Person
8	National Women's Law Center	*3,722*	2,698	Organization
9	Justice 4 Migrant Women	1,174	143	Organization
10	Alexandria Ocasio-Cortez	9,182	1,729	Person

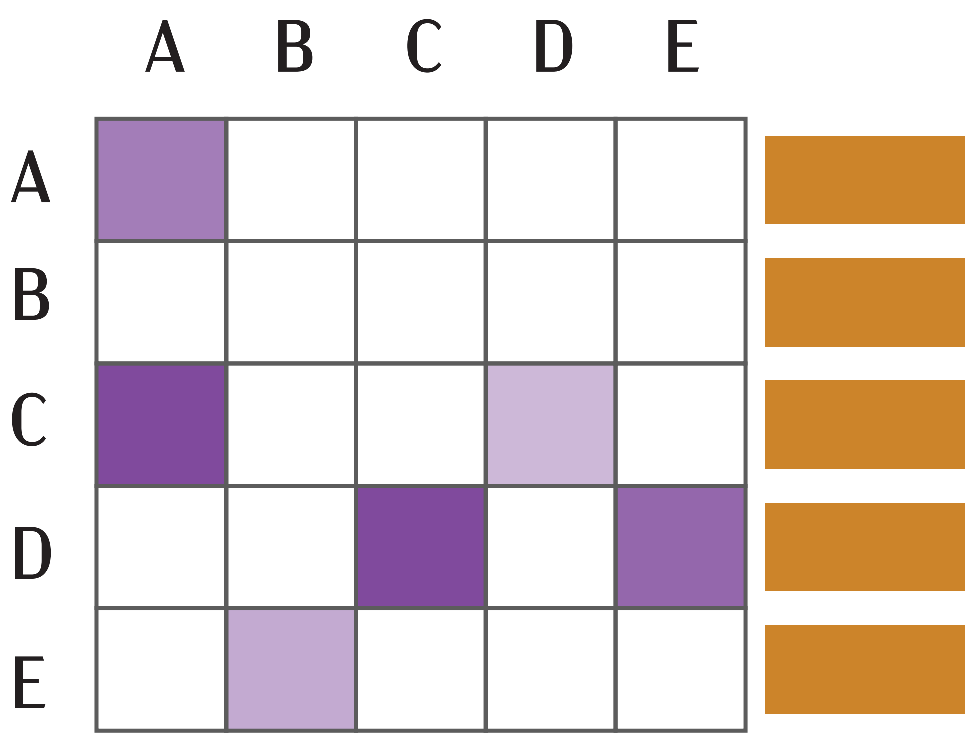
*real values except those in italics which have been reduced by a factor of 10 for the purpose of this activity

Edges

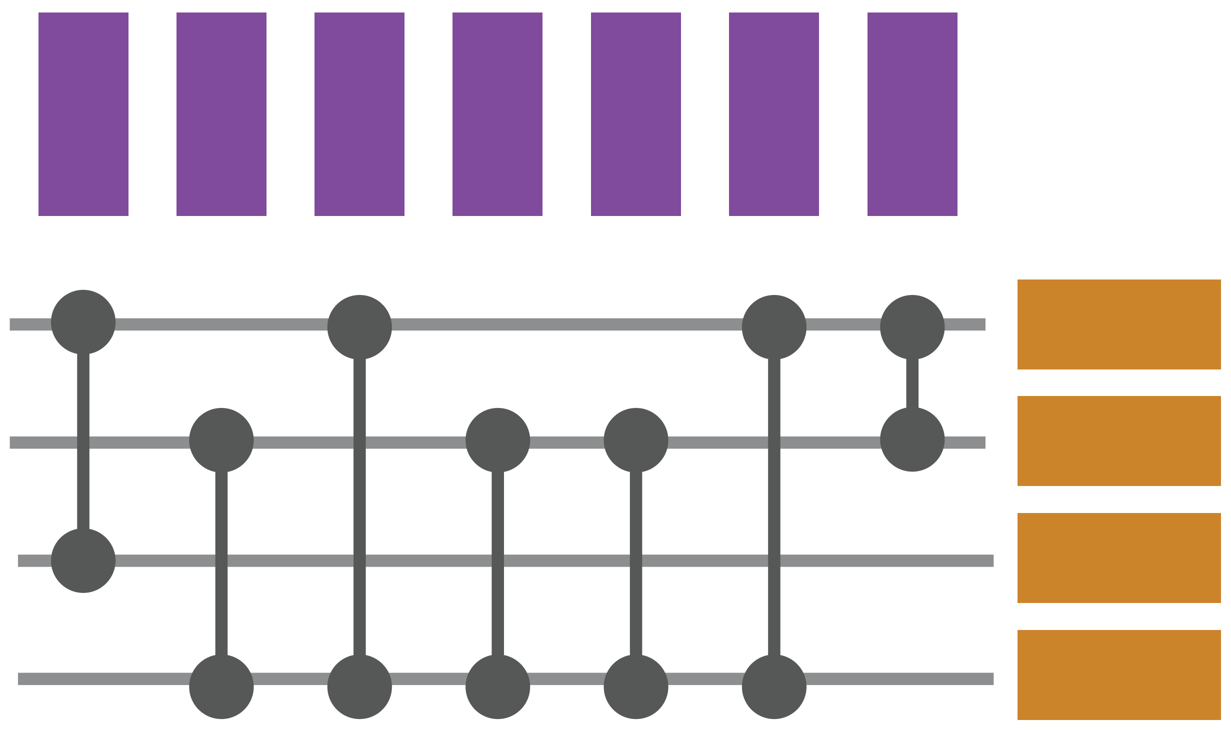
	Name	Name	Type	Frequency
1	Michelle Obama	Tina Chen	Mention	2
2	Michelle Obama	Time's Up	Mention	2
3	Michelle Obama	NowThis	Mention	2
4	Michelle Obama	Kerry Washington	Retweet	2
5	Time's Up	MeToo	Retweet	2
6	Time's Up	Tina Chen	Mention	2
7	Time's Up	Kerry Washington	Retweet	1
8	Time's Up	Justice for Migrant Women	Retweet	3
9	Tina Chen	Kerry Washington	Retweet	1
10	Tina Chen	Kerry Washington	Mention	1
11	MeToo	Monica Ramirez	Mention	1
12	MeToo	National Women's Law Center	Retweet	2
13	MeToo	Justice 4 Migrant Women	Retweet	1
14	Justice 4 Migrant Women	National Women's Law Center	Mention	1
15	Justice 4 Migrant Women	Monica Ramirez	Mention	1
16	Justice 4 Migrant Women	NowThis	Retweet	1
17	NowThis	Alexandria Ocasio-Cortez	Retweet	2

get your own twitter network @
bit.ly/twitter-network

Choose Adj Matrix or Biofabric



Adjacency Matrix



BioFabric

Nodes

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2	Tina Tchen	428	173	Person
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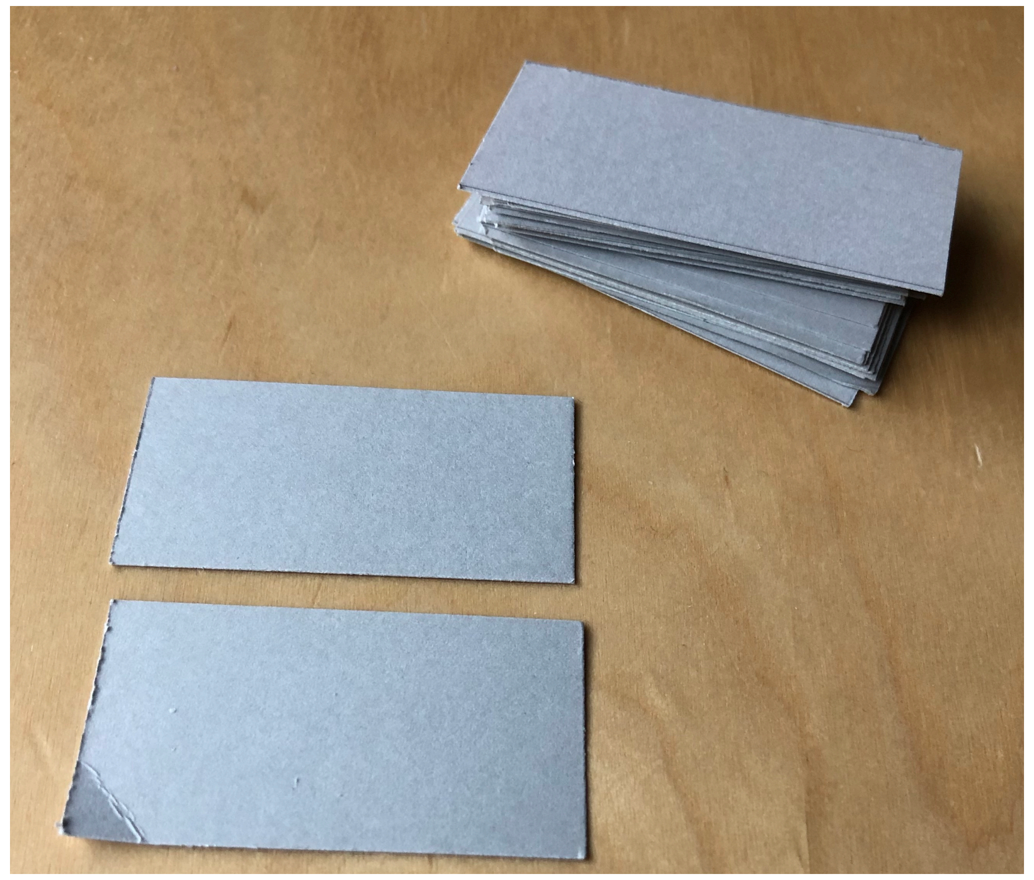
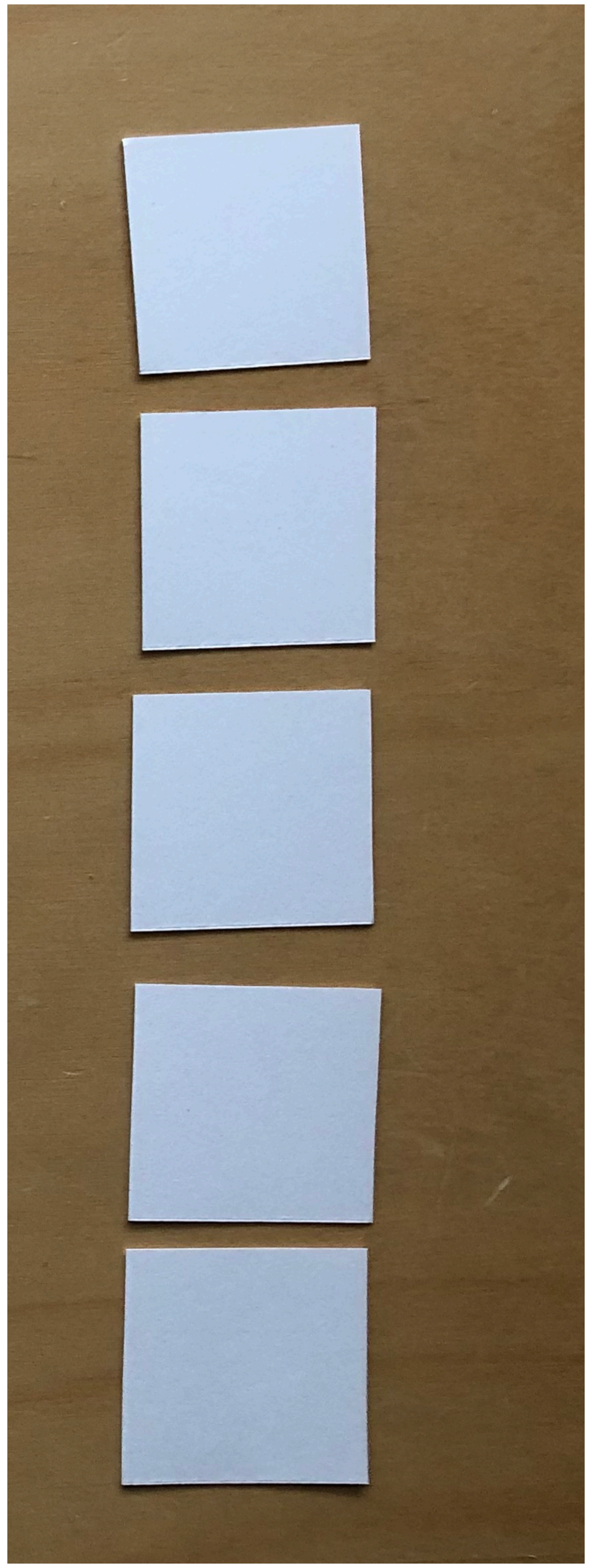
6	Time's Up	Tina Chen	Mention	2
7	Time's Up	Kerry Washington	Retweet	1
8	Time's Up	Justice for Migrant Women	Retweet	3
9	Tina Chen	Kerry Washington	Retweet	1
10	Tina Chen	Kerry Washington	Mention	1
11	MeToo	Monica Ramirez	Mention	1
12	MeToo	National Women's Law Center	Retweet	2
13	MeToo	Justice 4 Migrant Women	Retweet	1
14	Justice 4 Migrant Women	National Women's Law Center	Mention	1
15	Justice 4 Migrant Women	Monica Ramirez	Mention	1
16	Justice 4 Migrant Women	NowThis	Retweet	1
17	NowThis	Alexandria Ocasio-Cortez	Retweet	2

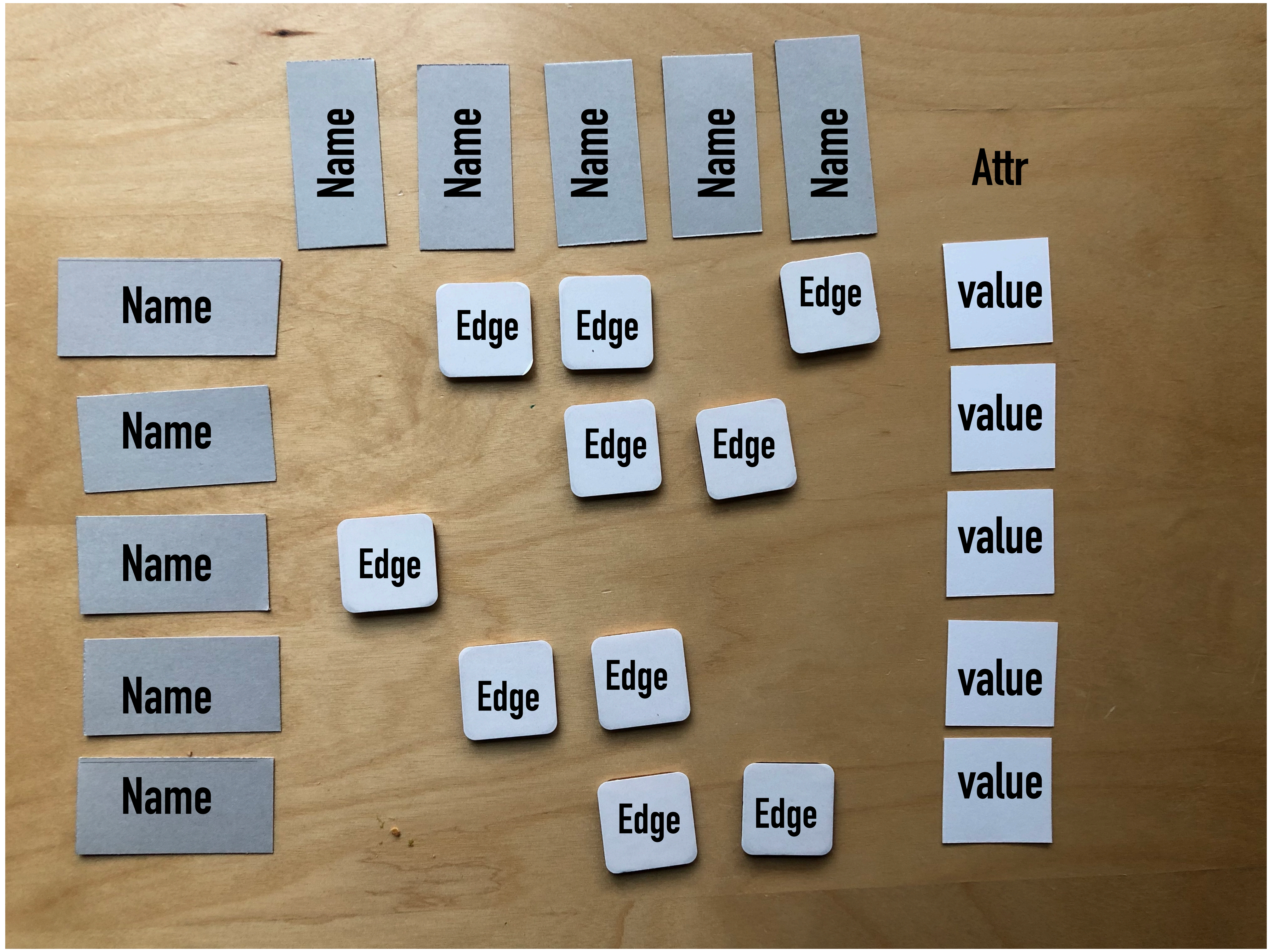


Node Labels

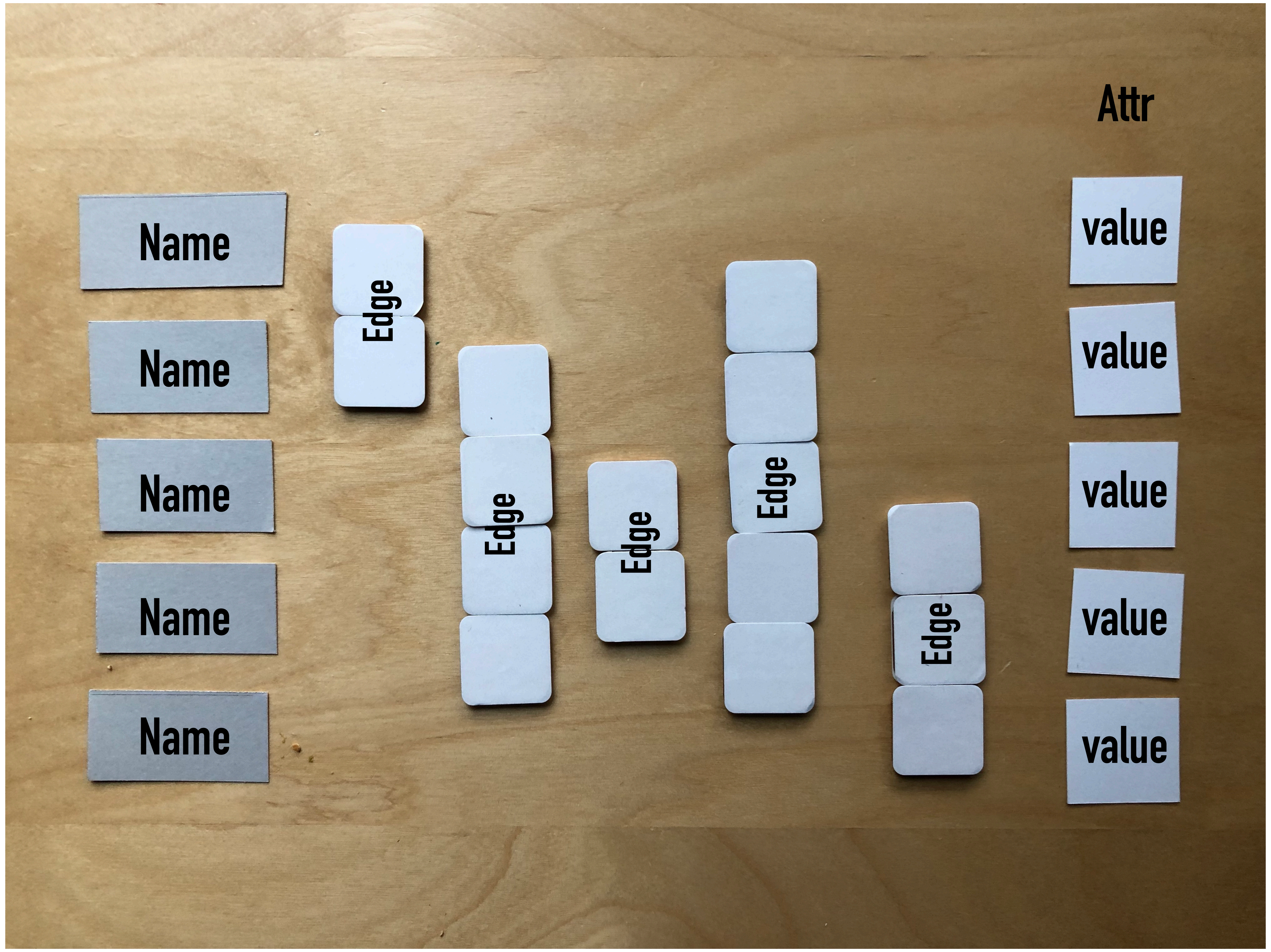
Edge Tokens

Node Attribute Squares





Adjacency Matrix



Biofabric

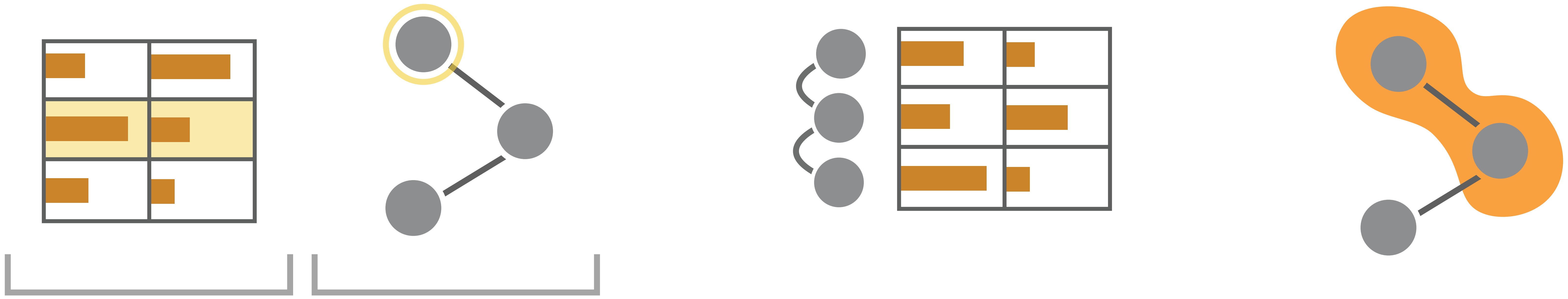
20 minutes

Move to your neighbor's matrix/fabric

How many tweets does the person who has the most connections in this graph have?

Does the person with the least tweets have more interactions of type retweet or mention?

View Operations

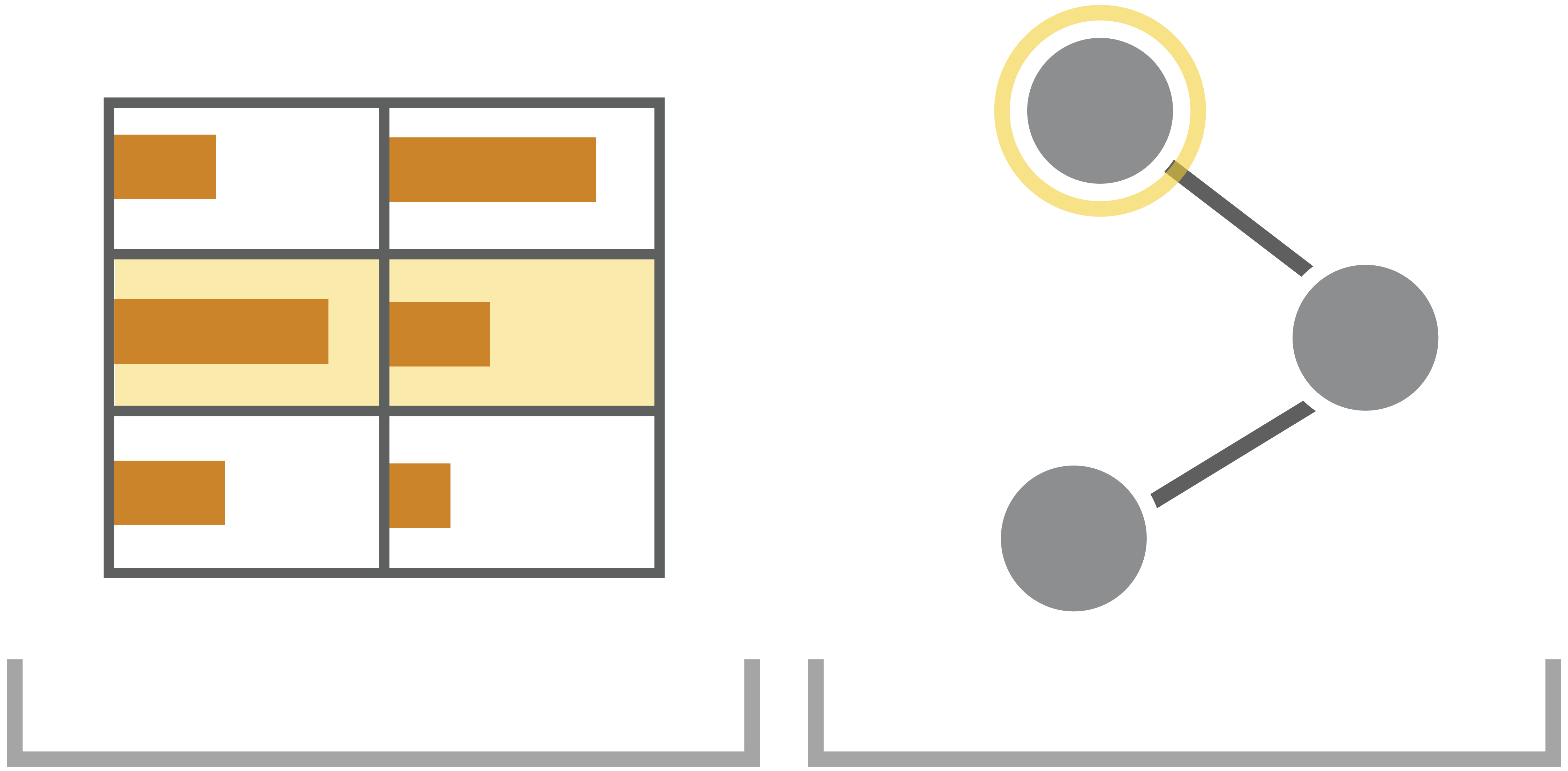


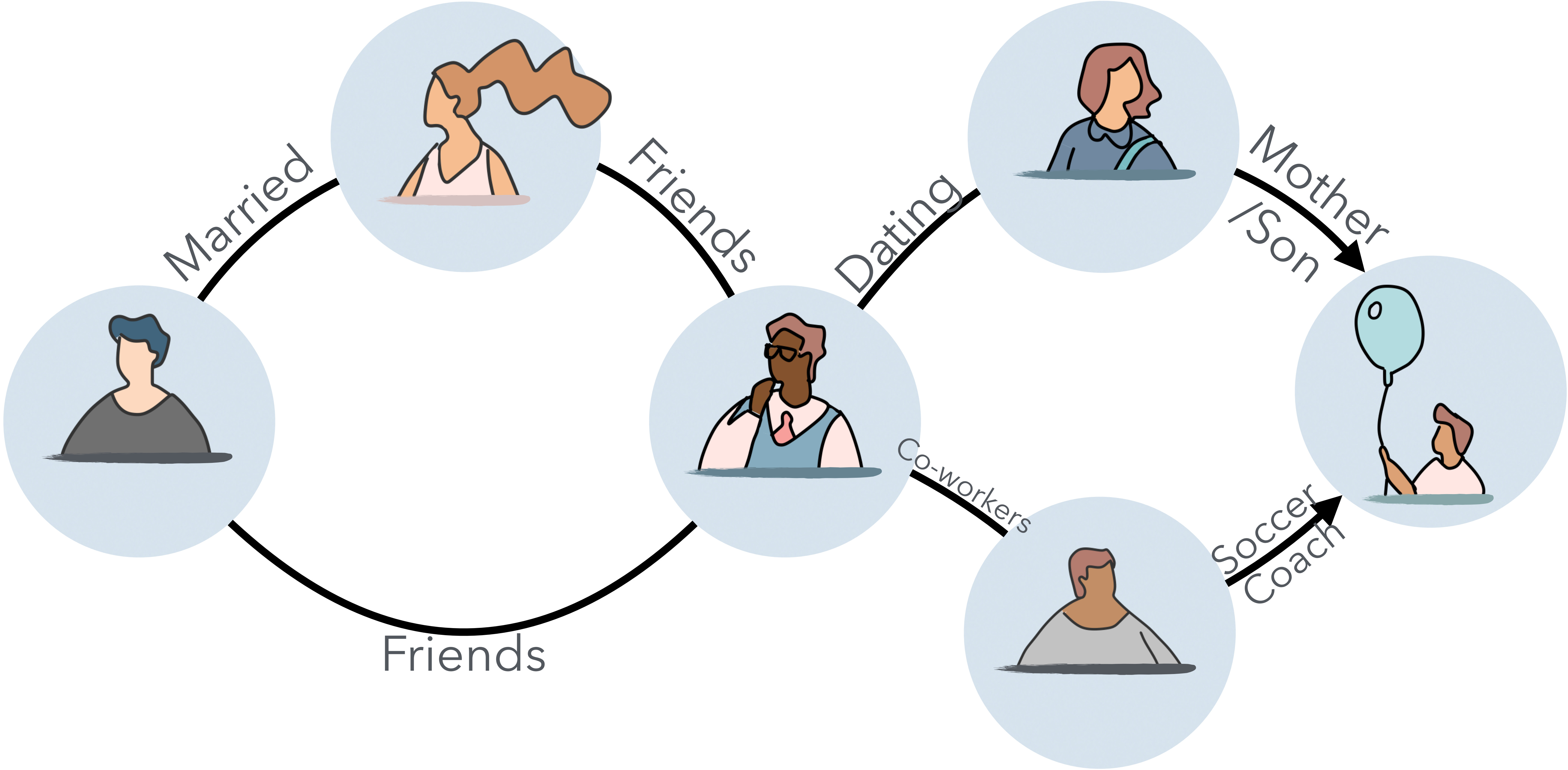
Juxtaposed

Integrated

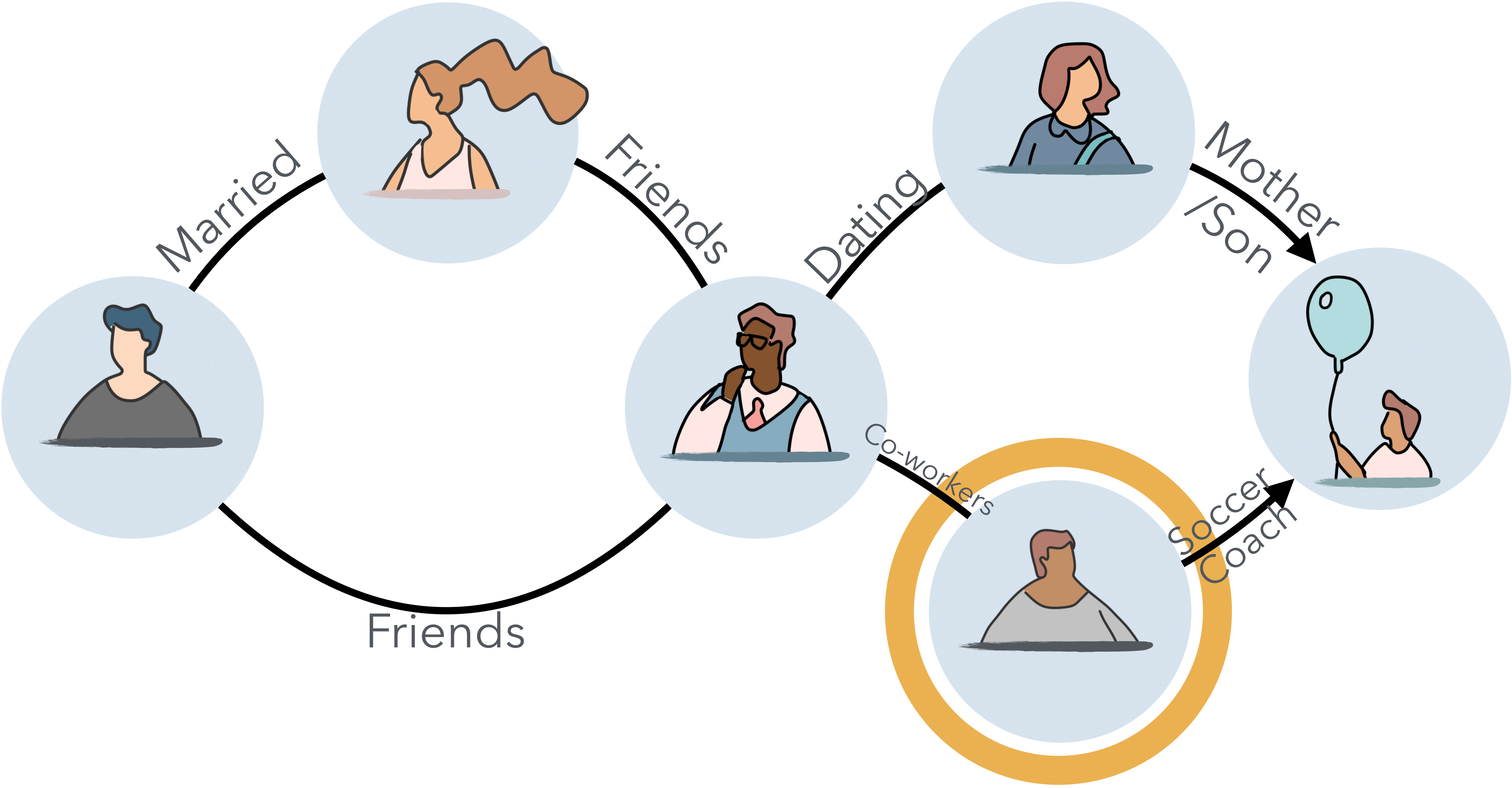
Overloaded

Juxtaposed

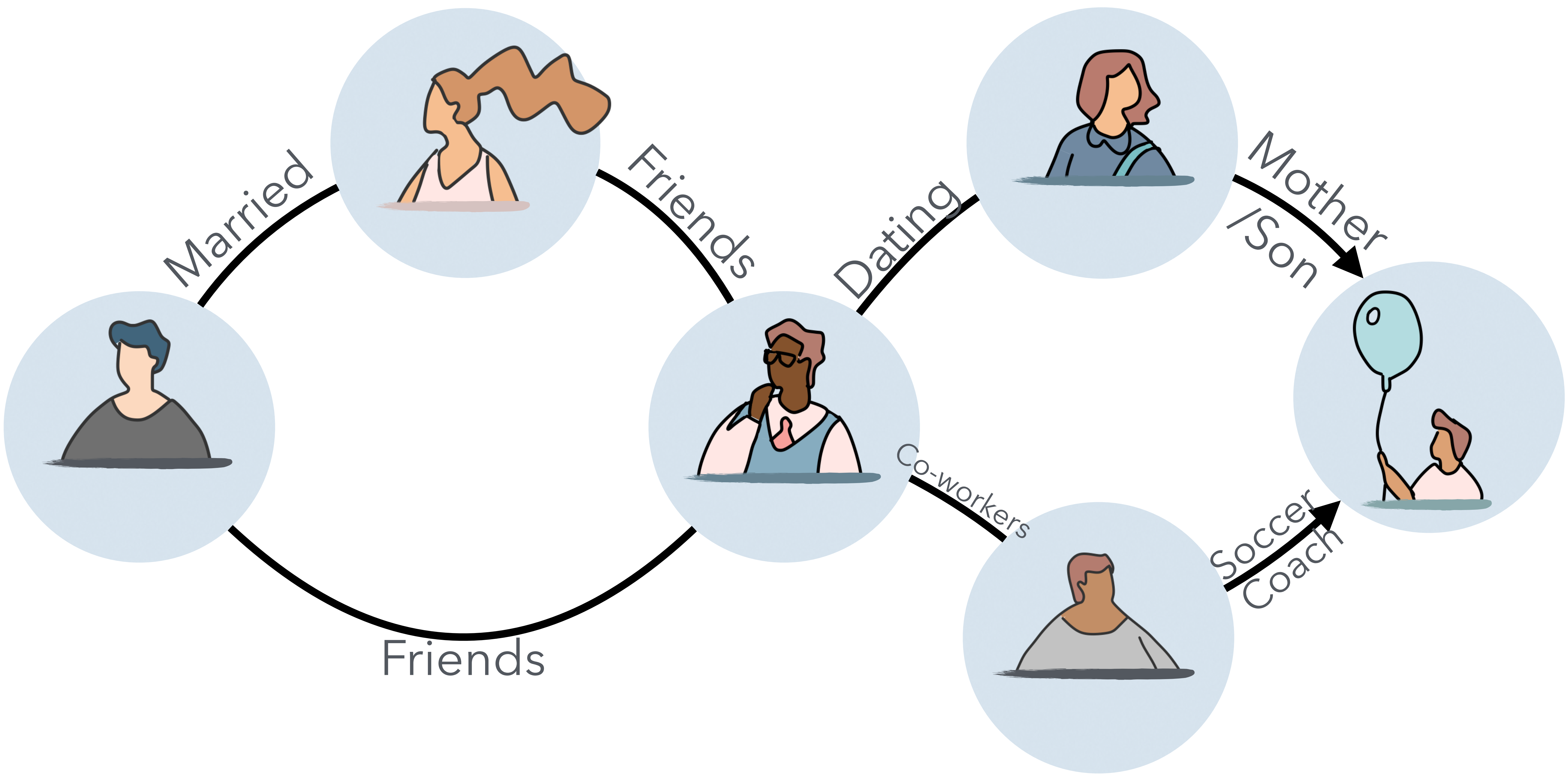




Married
Friends
Friends
Dating
Mother
/Son
Co-workers
Soccer
Coach



Name	Beverage	Day 1
Mark	Beer	1
Sue	Coke	0
Cole	Port	4
Jon	Coke	5
Tom	Beer	2
Abby	Port	3



Name	Beverage	Day 1
Mark	Beer	1
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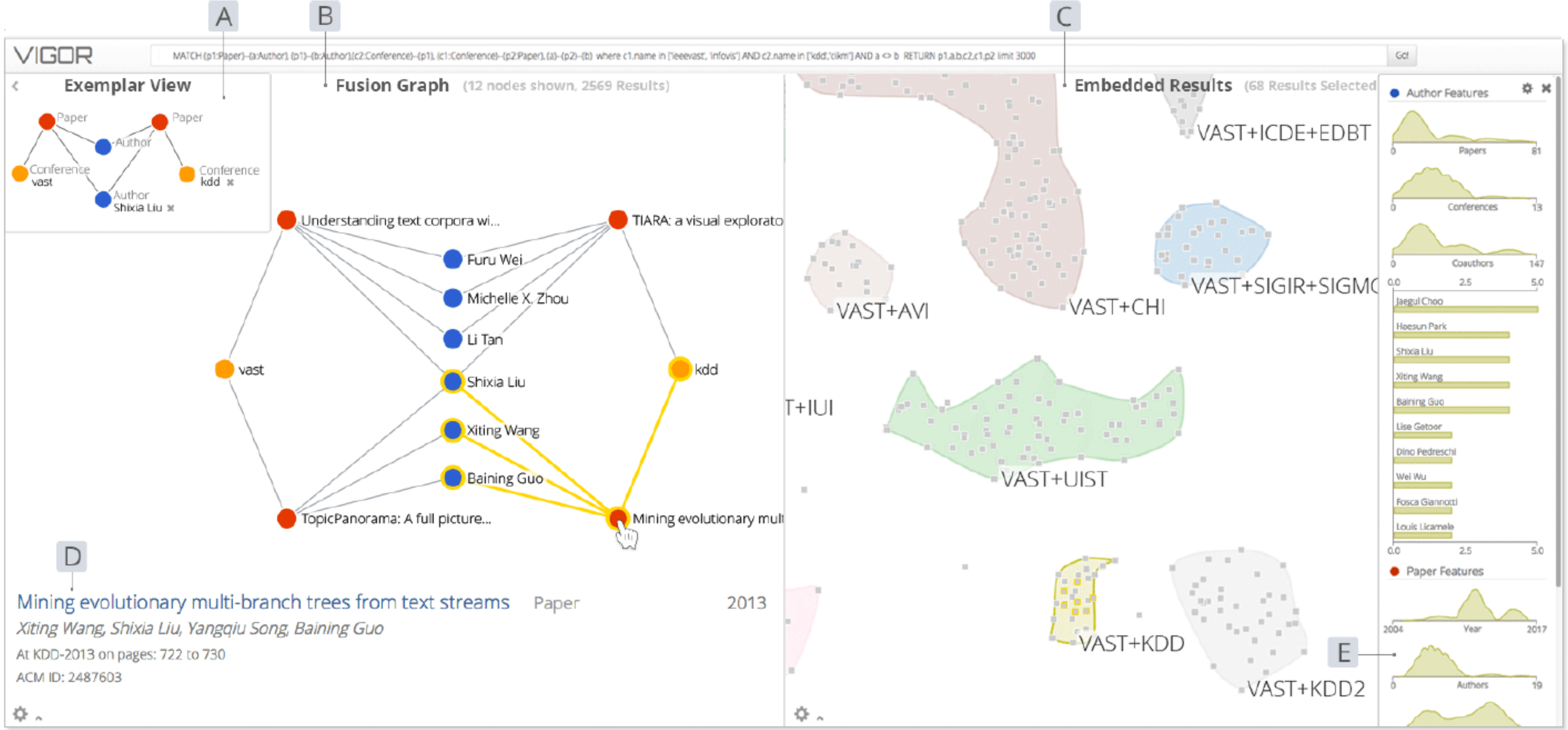
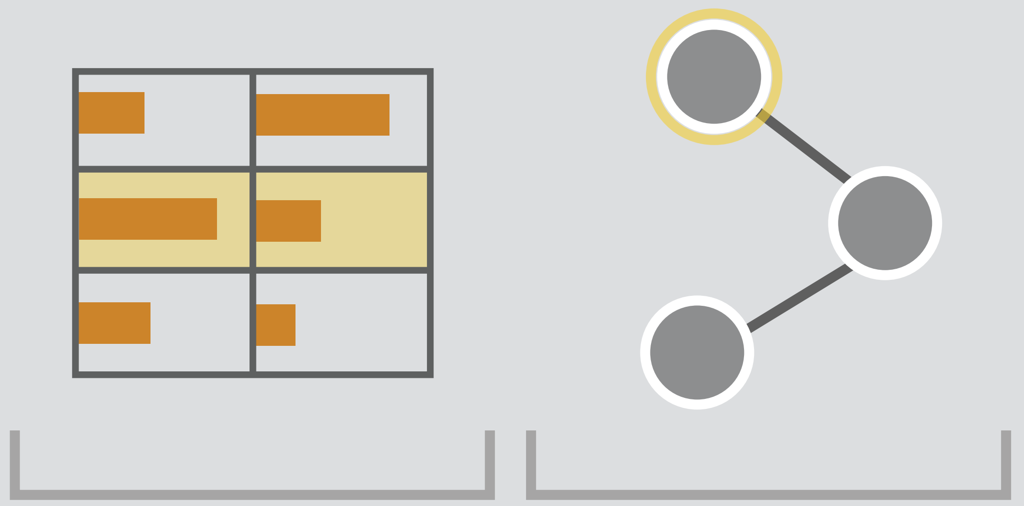
Tom	Beer	2
Abby	Port	3

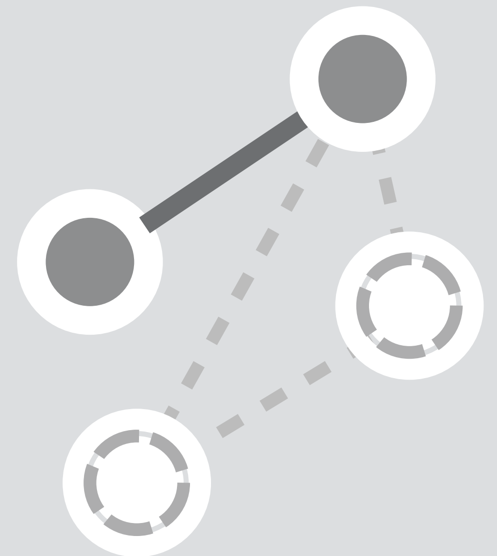
Relationship	Years
Dating	4
Mother / Son	12
Co-workers	3
Soccer Coach	2
Friends	8
Friends	3
Married	4



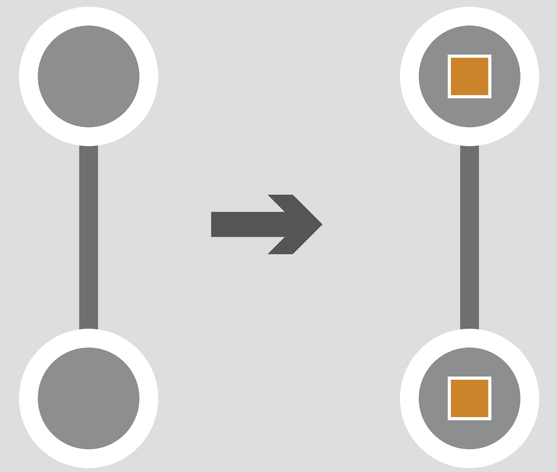
VIGOR *Pienta et al. 2018*



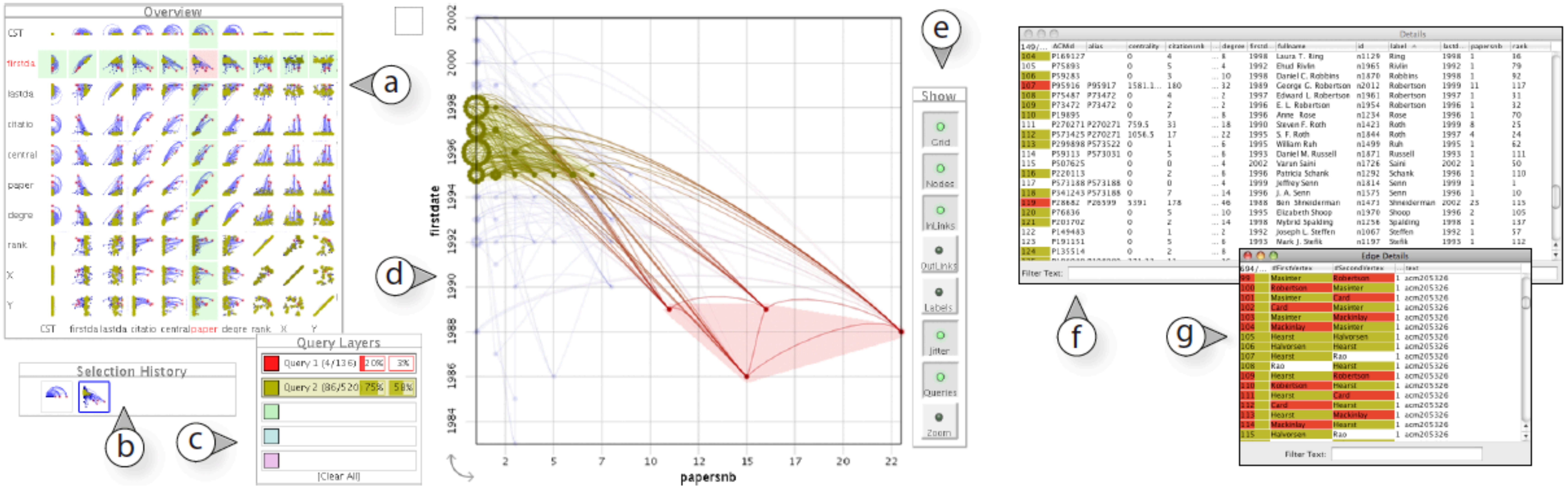
Juxtaposed

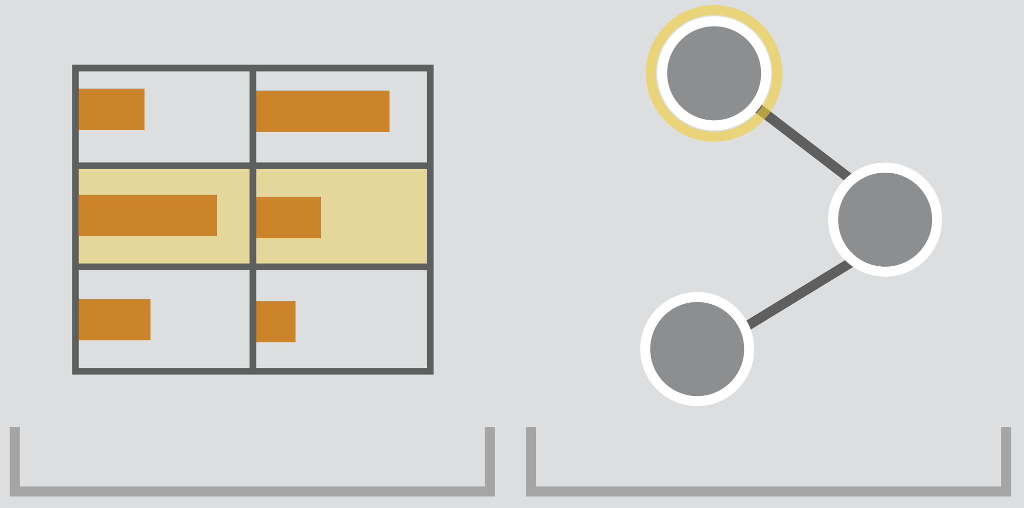


Querying and Filtering



Deriving New Attributes

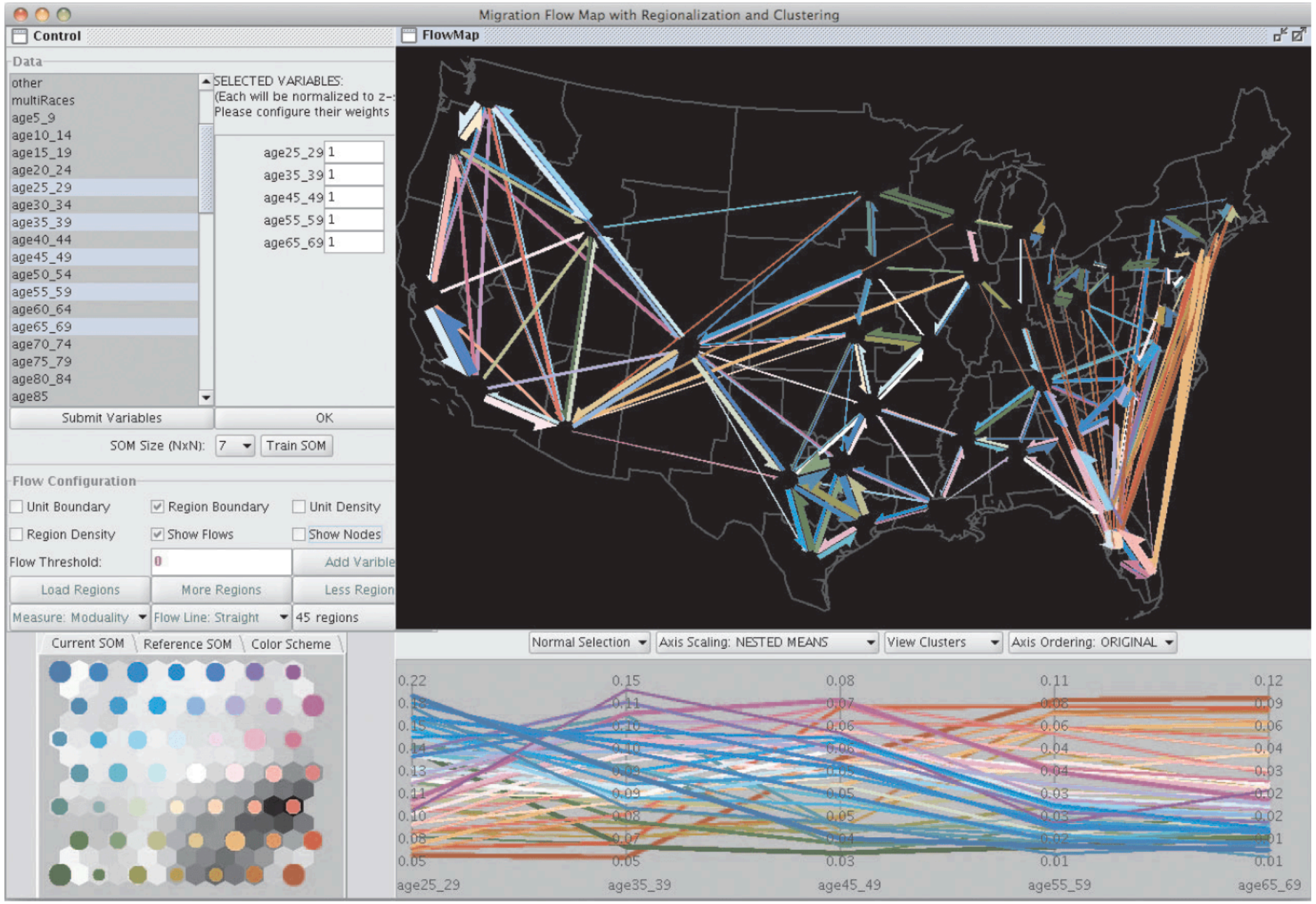


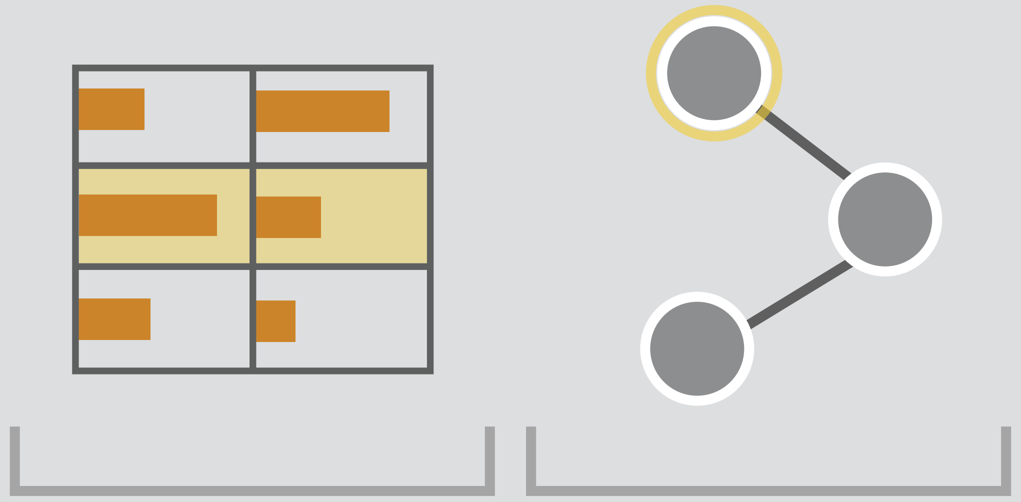


Juxtaposed

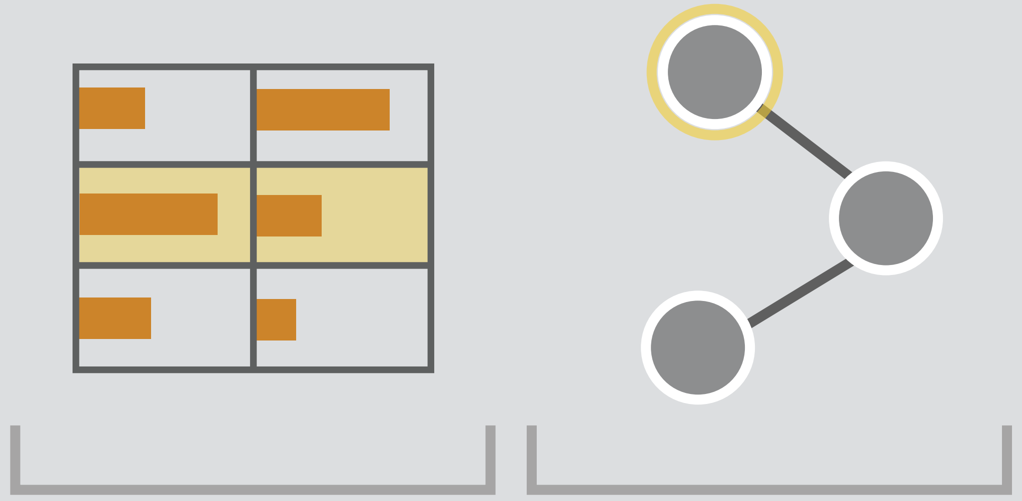
Graph Dice *Bezerianos et al. 2010*

Guo, 2009

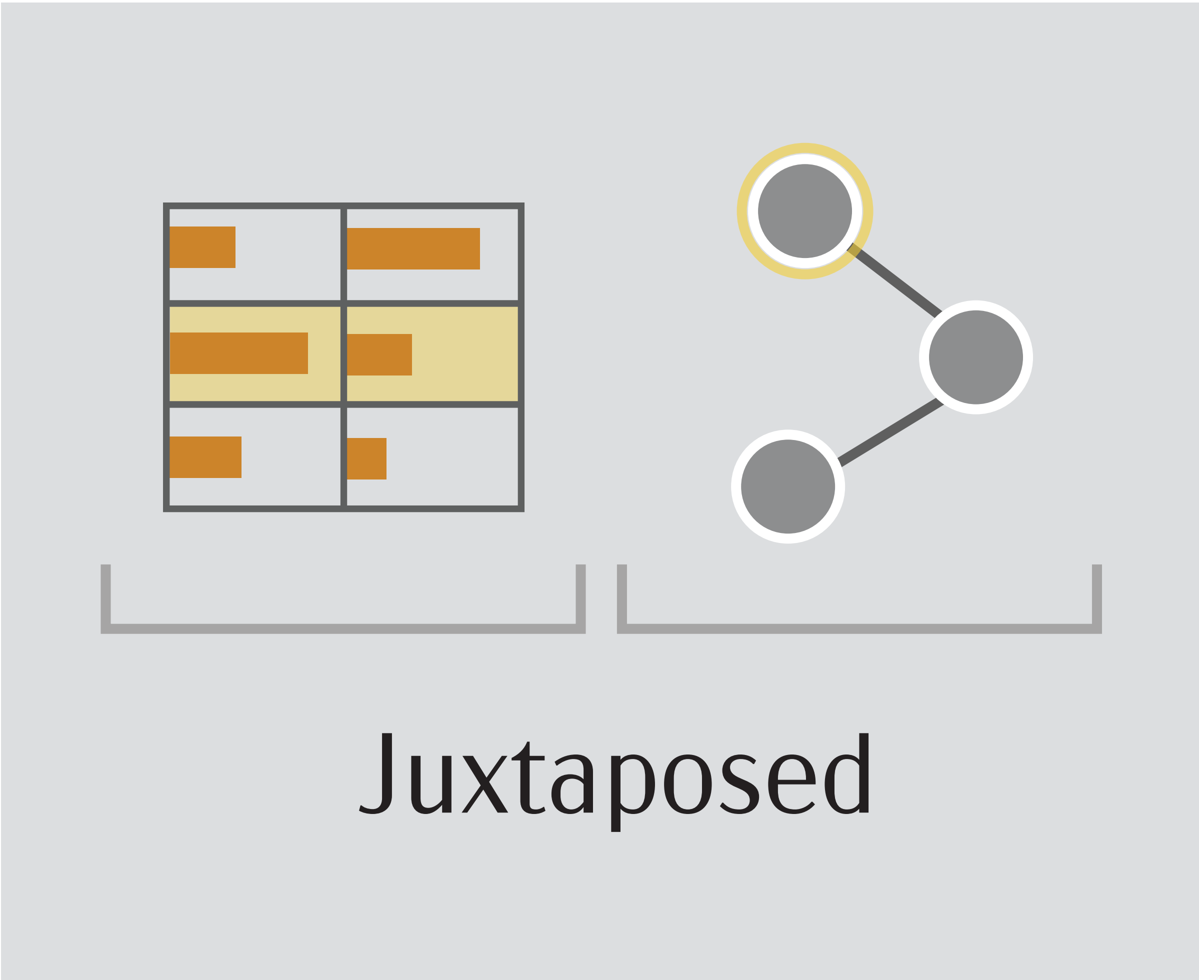




Juxtaposed



Juxtaposed

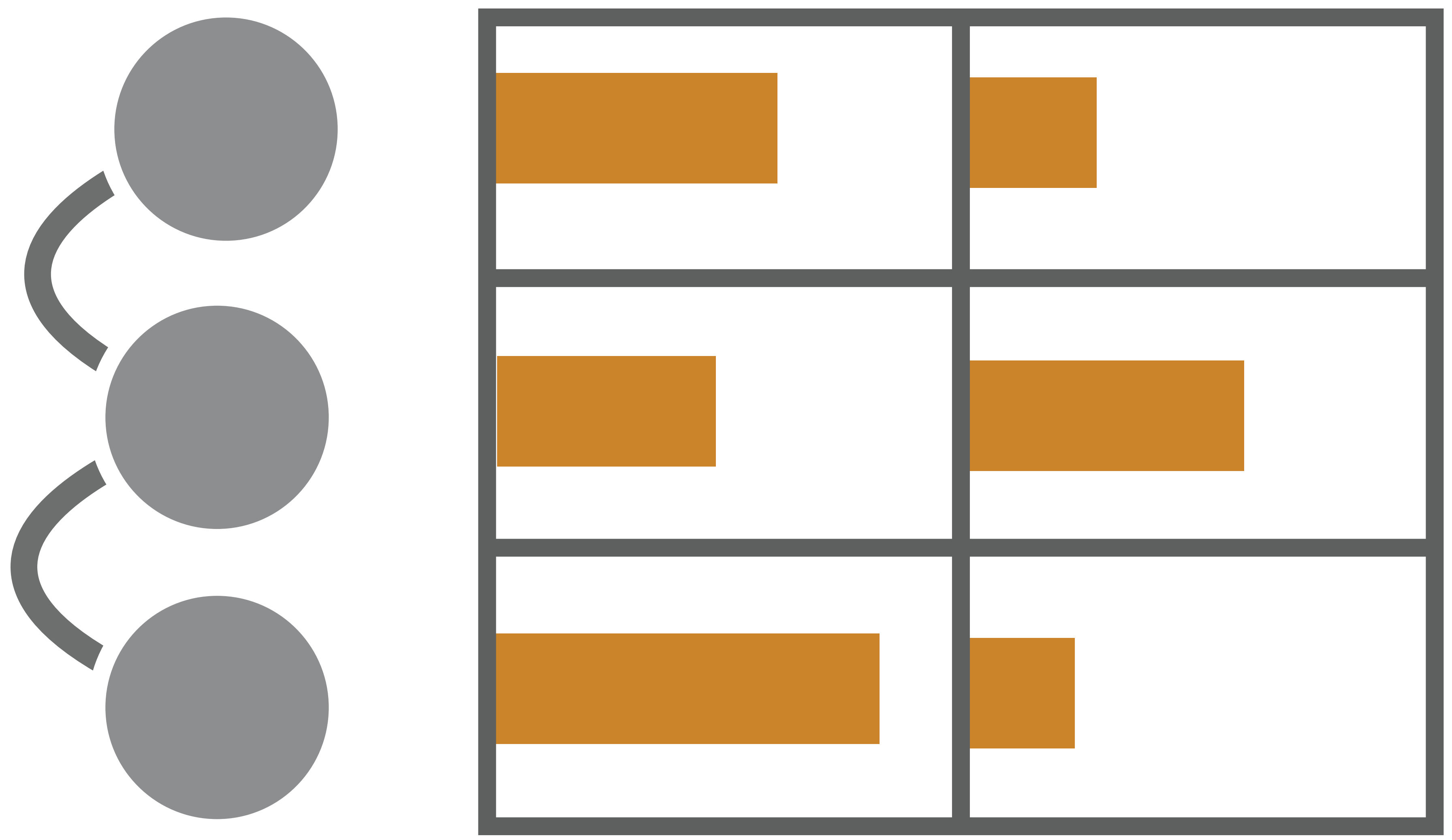


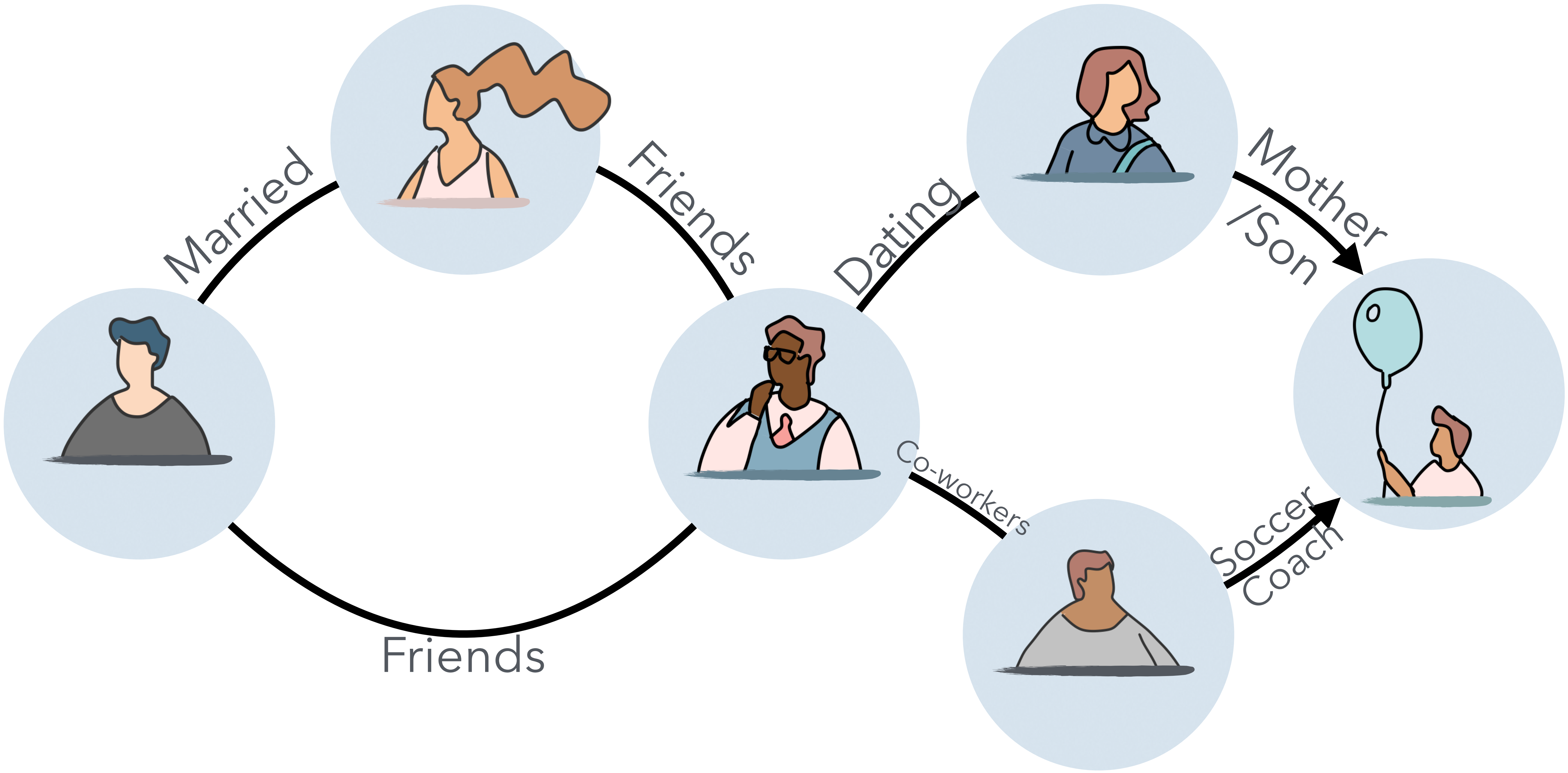
Independent views can optimize for topology and attribute independently.

Not great for tasks on topological structures beyond a single node or edge.

Recommended for large networks and/or very large numbers or heterogeneous types of node and link attributes

Integrated





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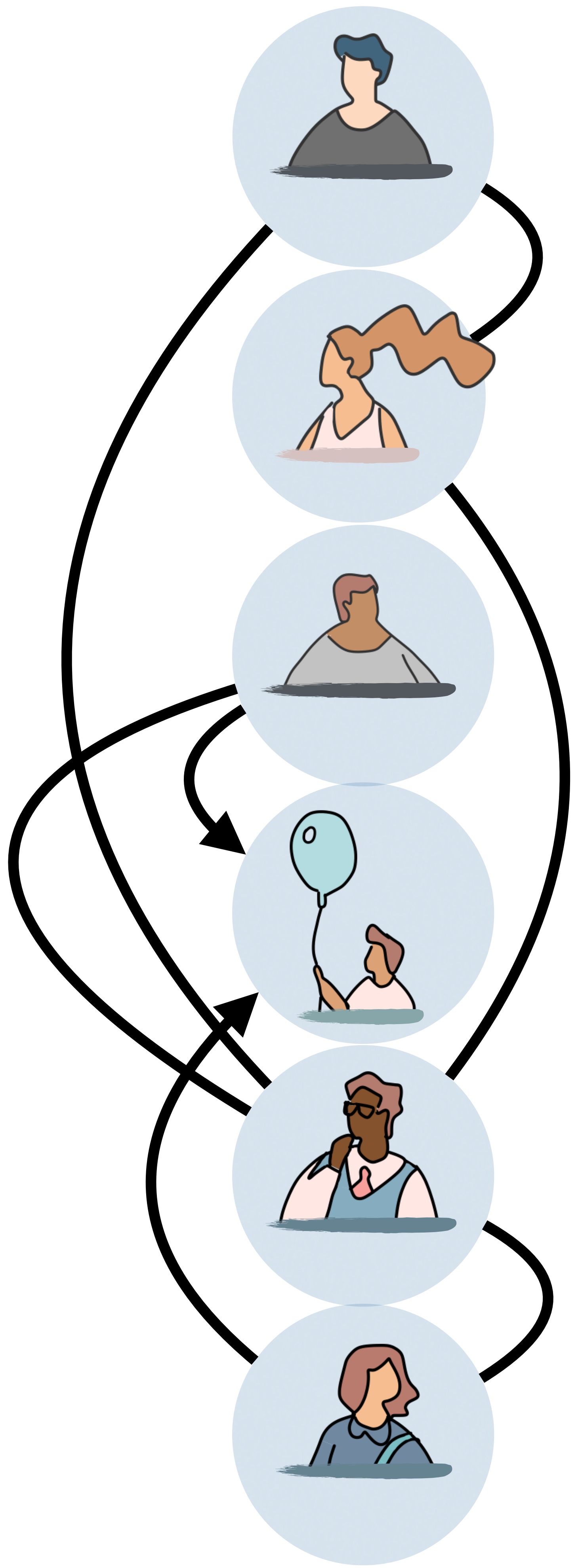

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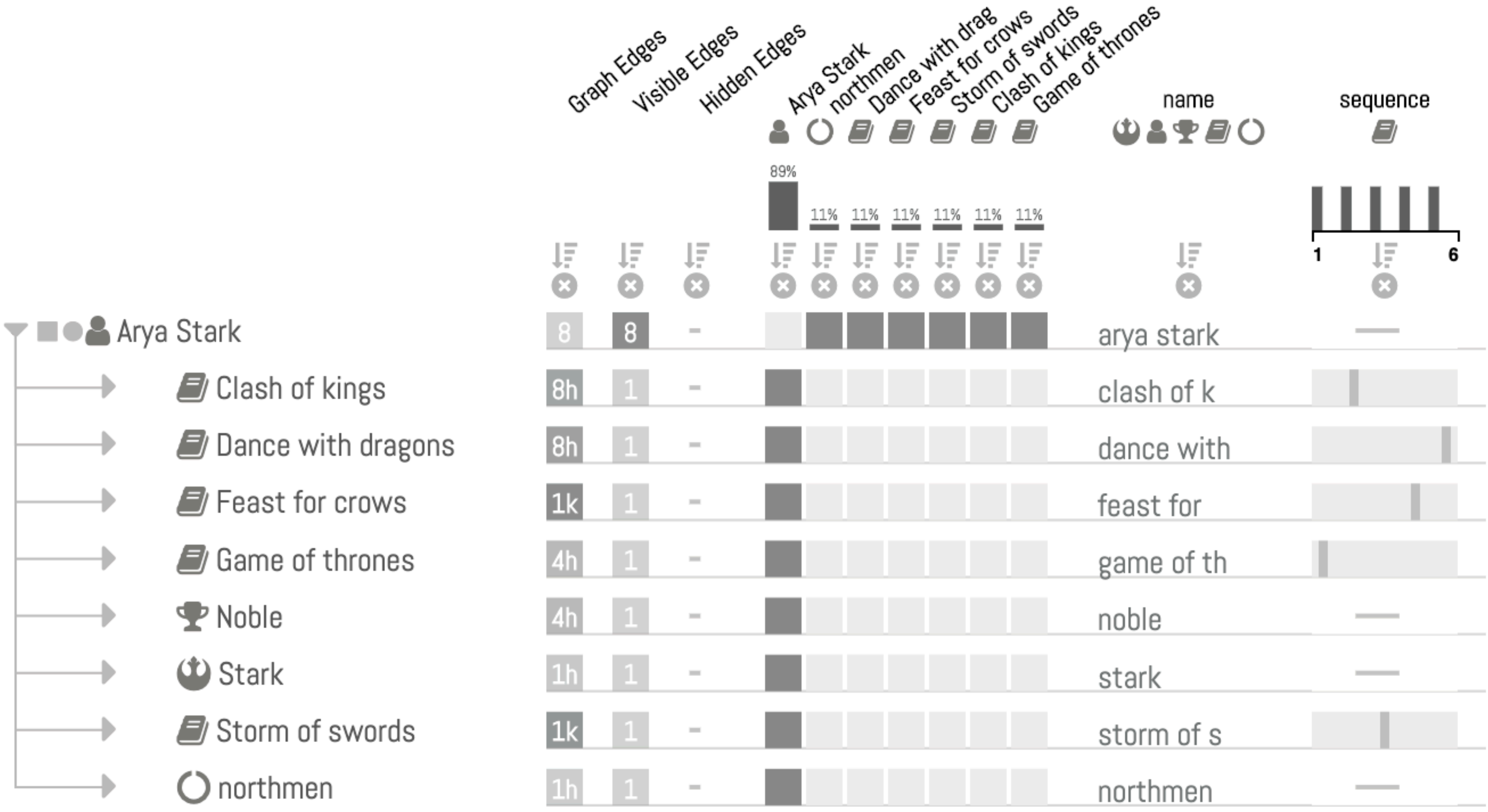
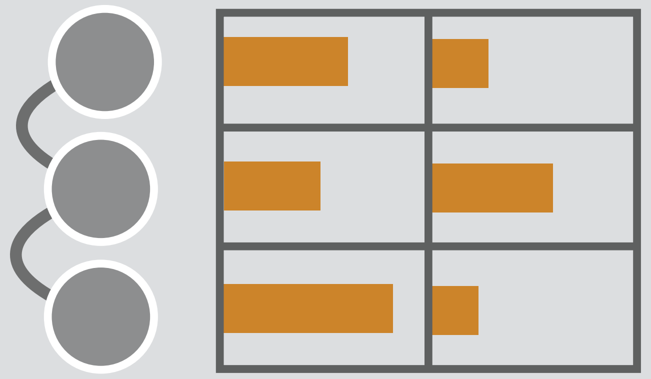
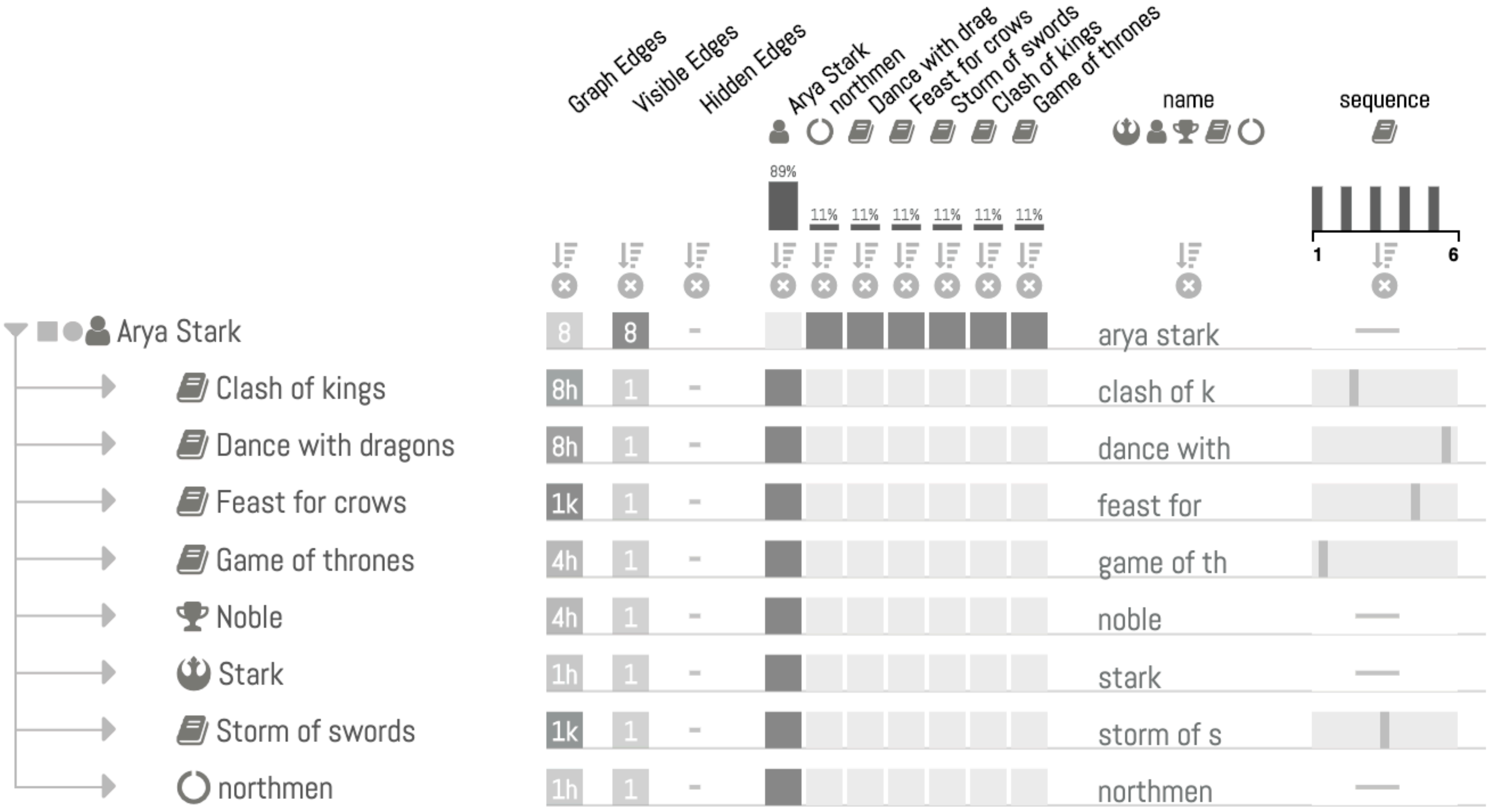


Juniper *Nobre et al. 2018*



Integrated



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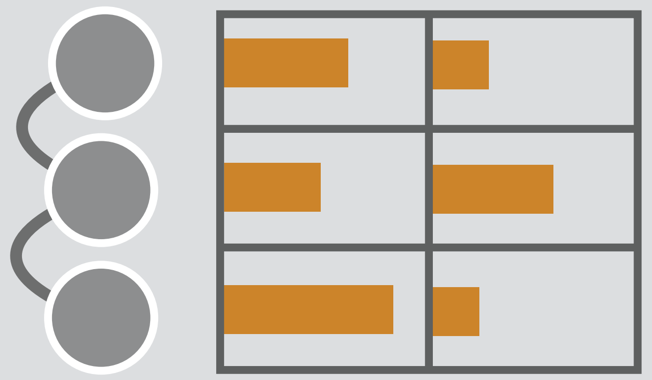

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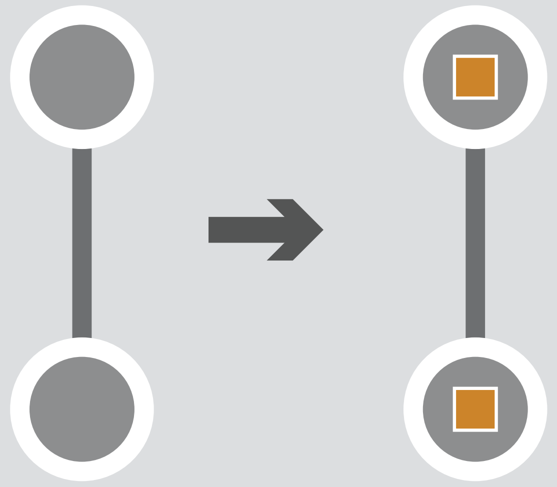

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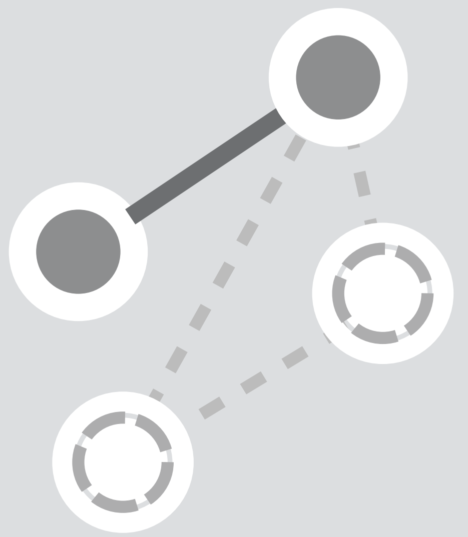
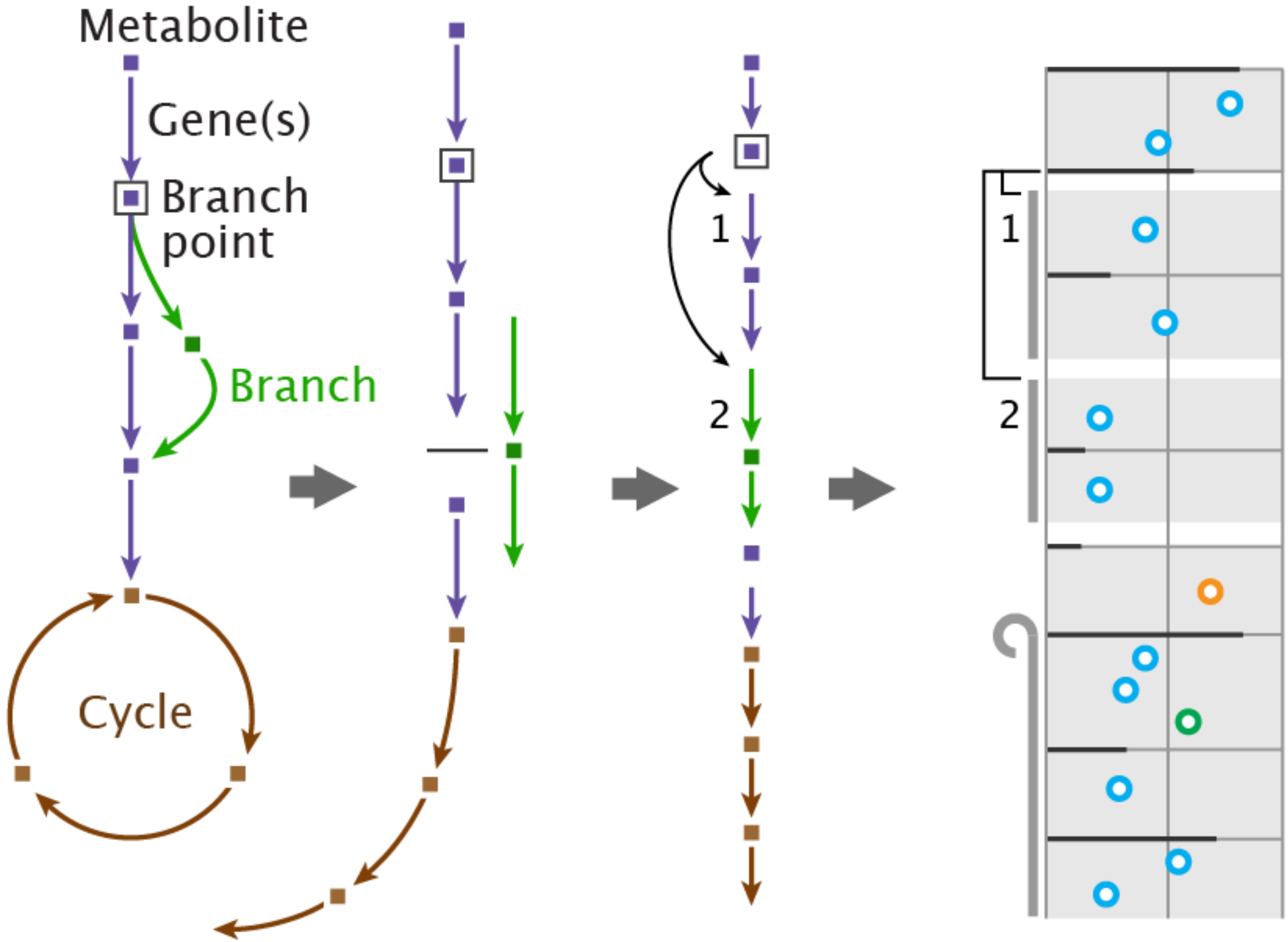
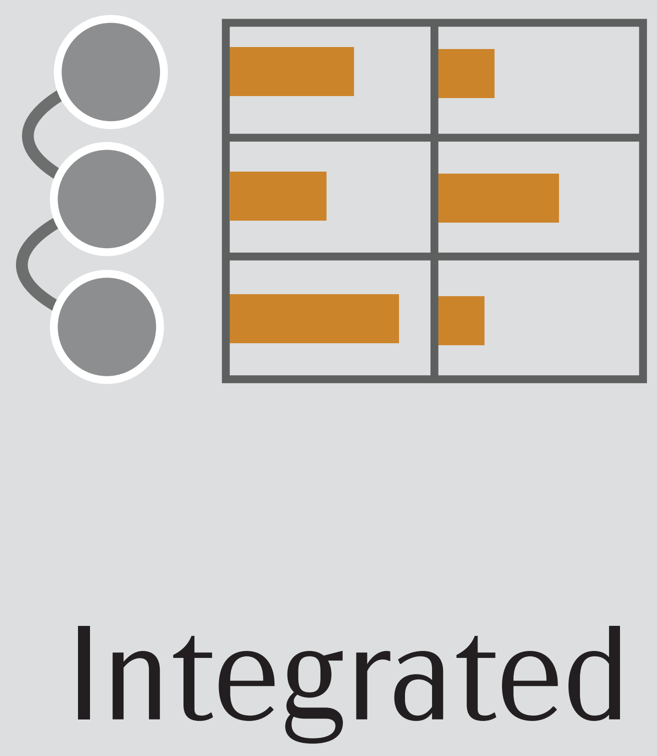
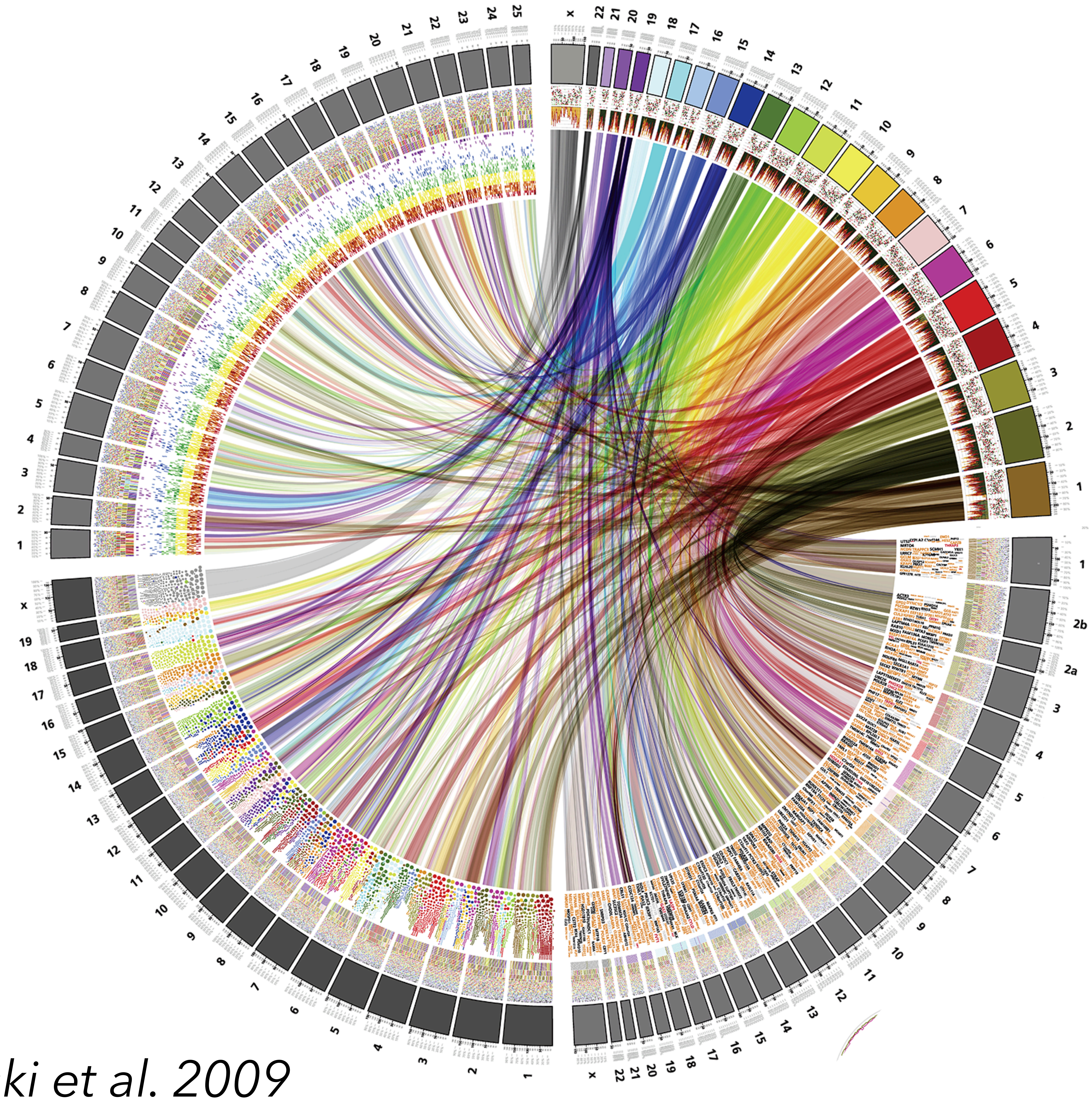


Querying and Filtering



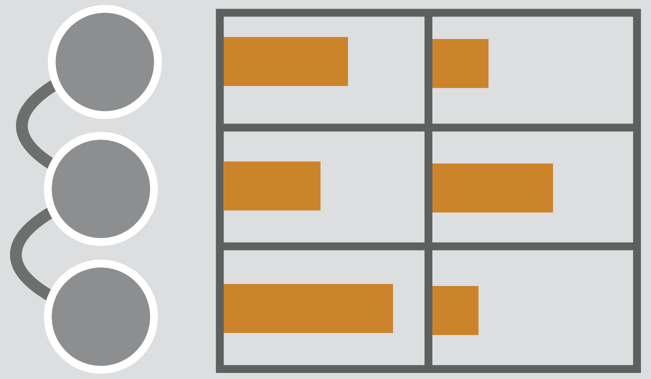
Pathline Meyer *et al. 2010*





Circos

Krzywinski et al. 2009



Integrated

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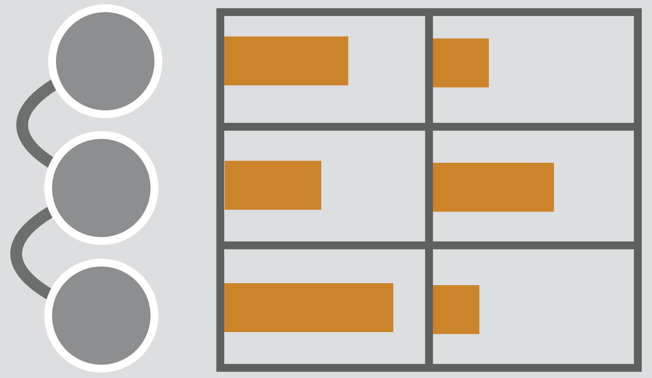


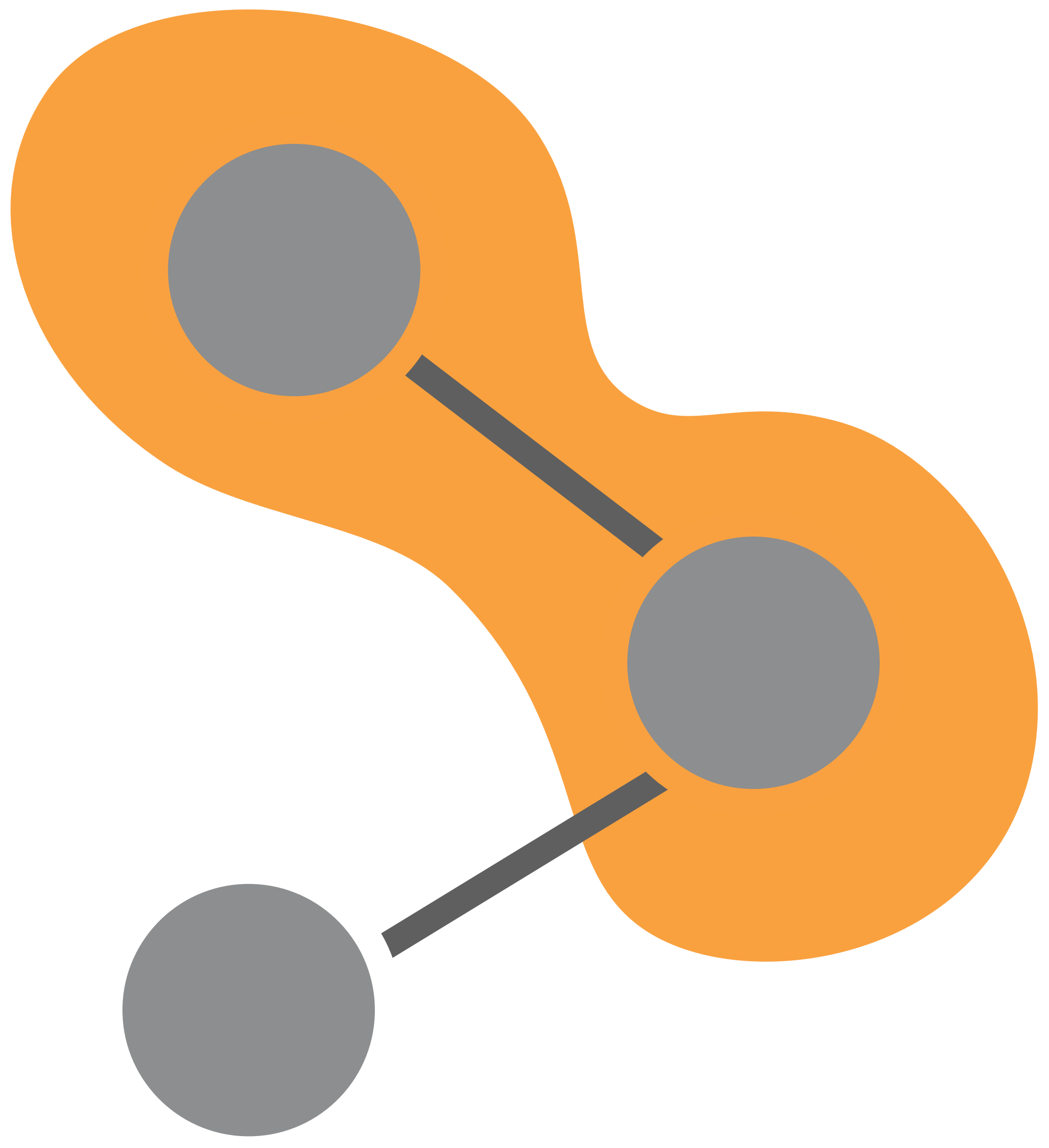
Integrated

good at integrating attributes with topology, if the topology can be represented in a linear layout.

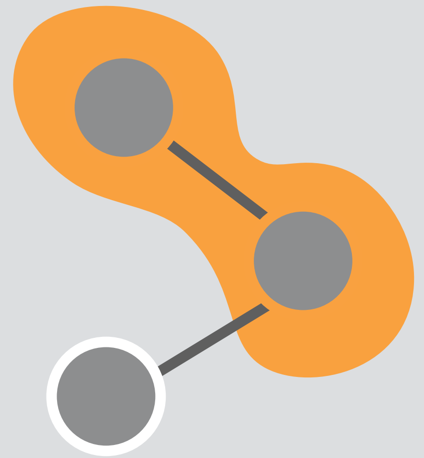
Not suitable for networks that can not be sensibly linearized.

Recommended for networks with several, heterogenous, node attributes and well suited for tasks on single nodes, neighbors, and paths

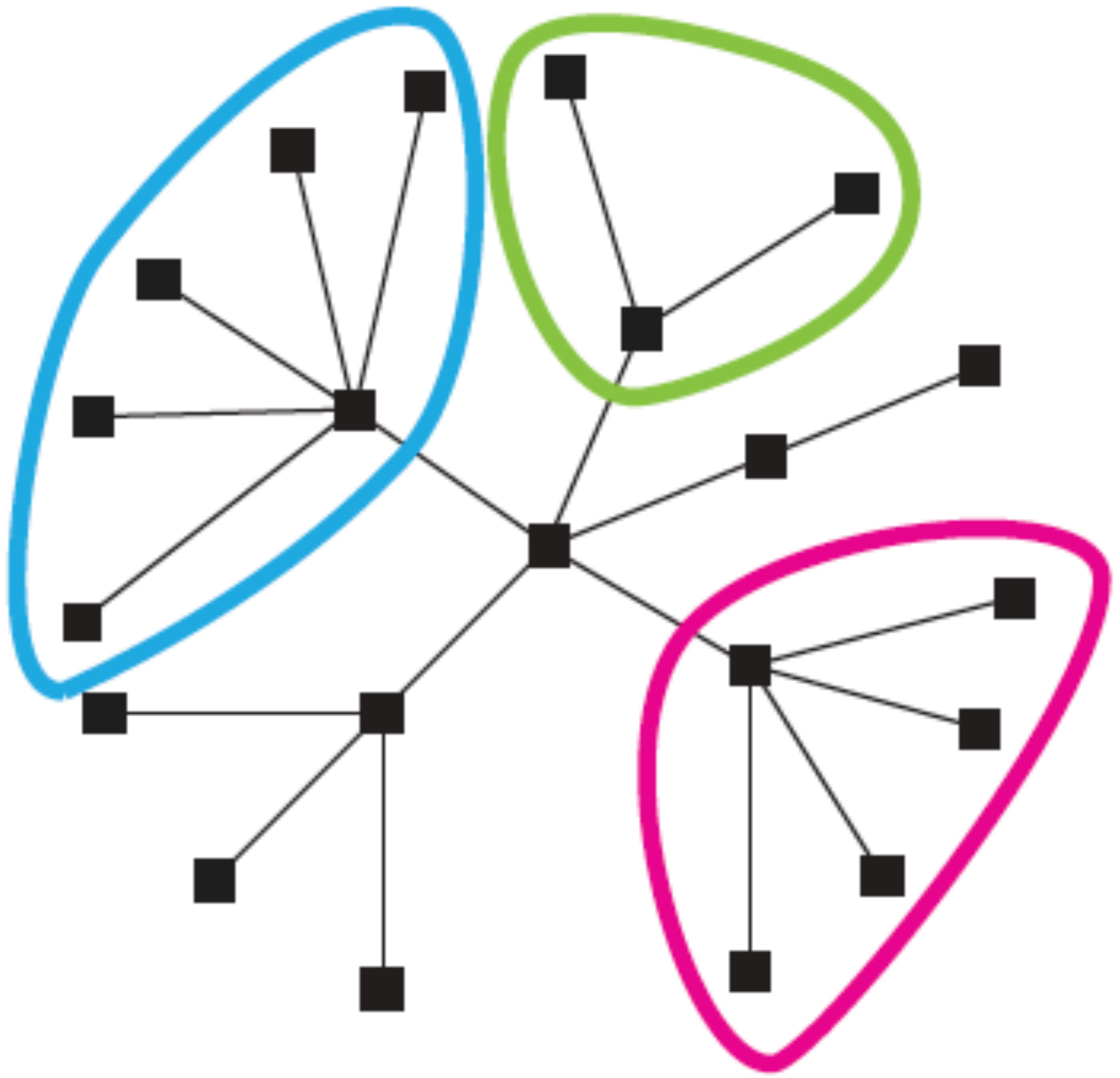
Overloaded

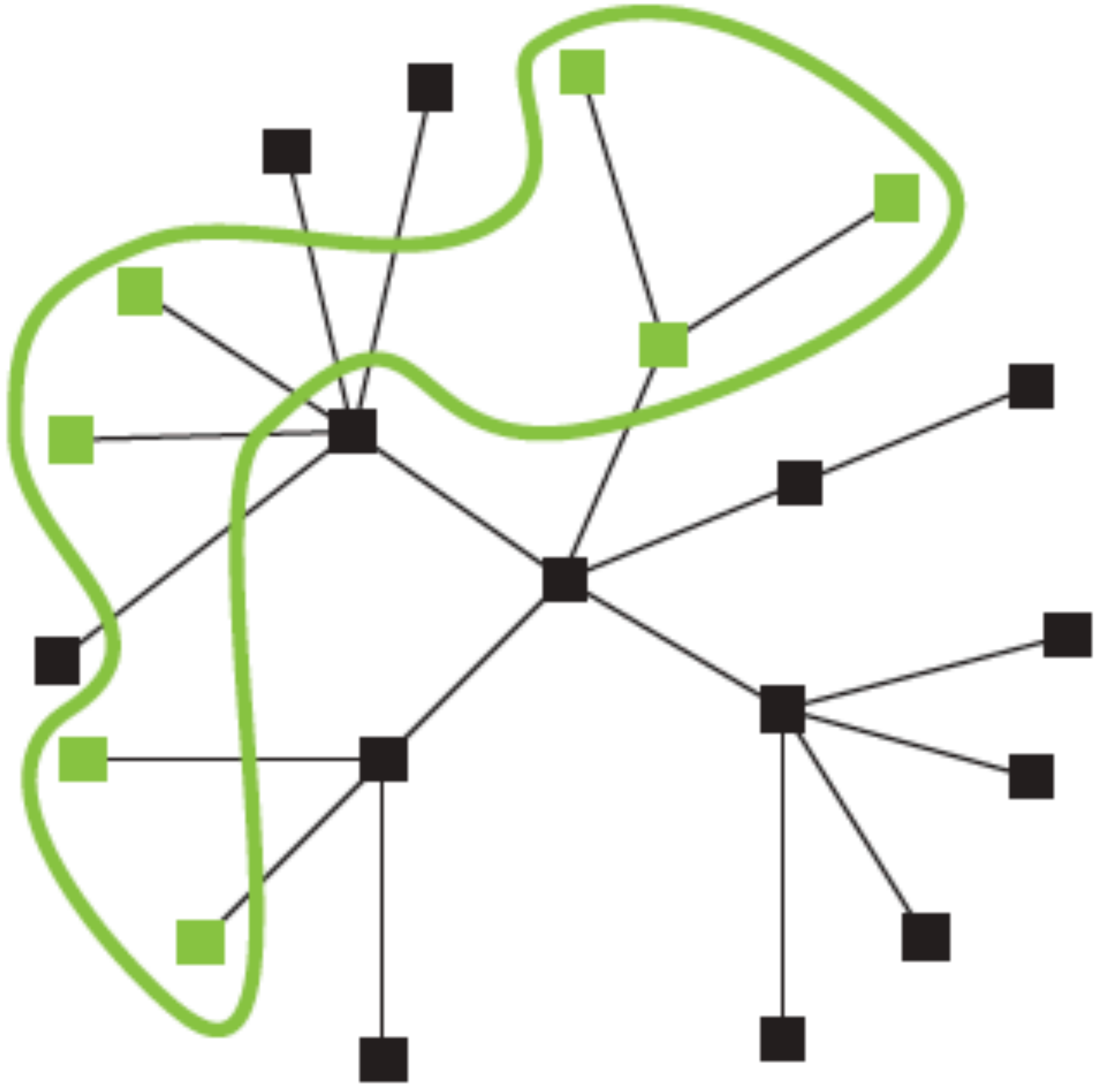


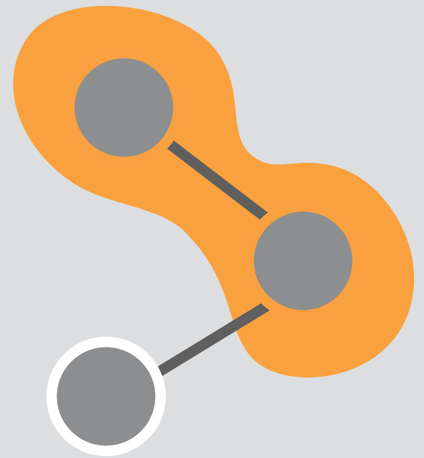
GMaps *Gansner et al. 2010*



Overloaded

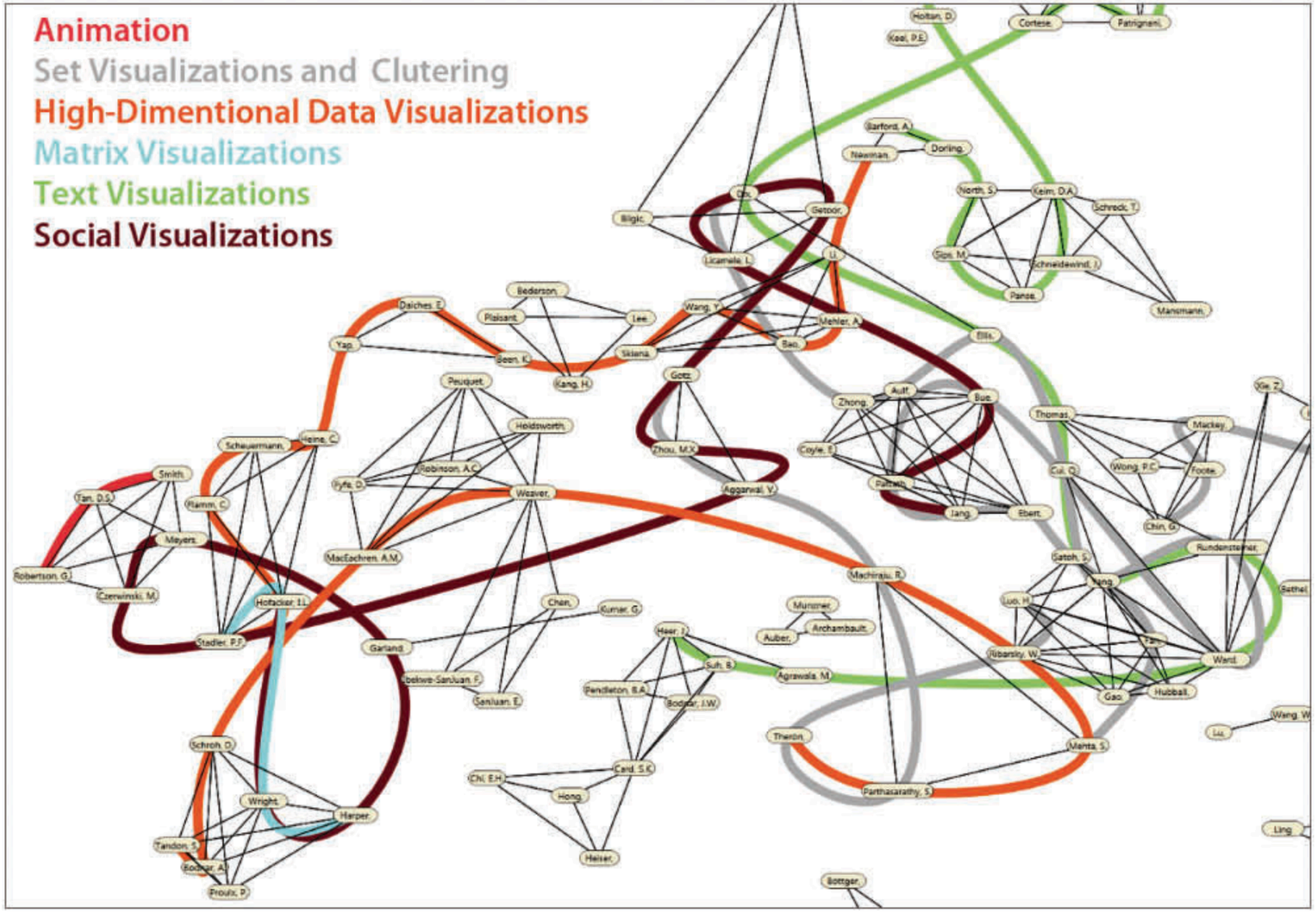




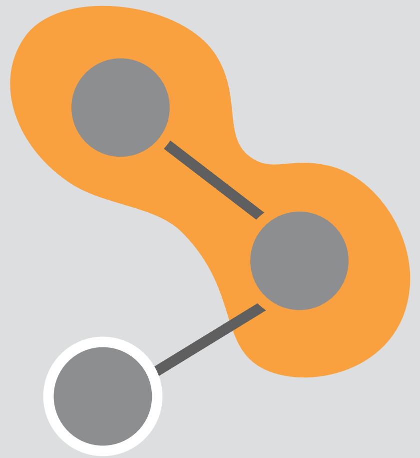


Overloaded

Bubble Sets *Collins et al. 2009*

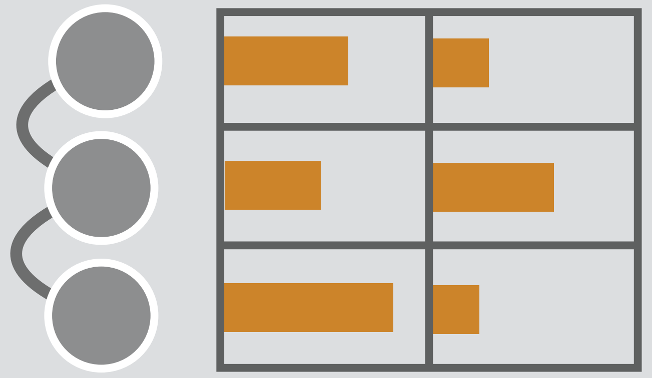


LineSets *Alper et al. 2011*



Overloaded

Overloaded



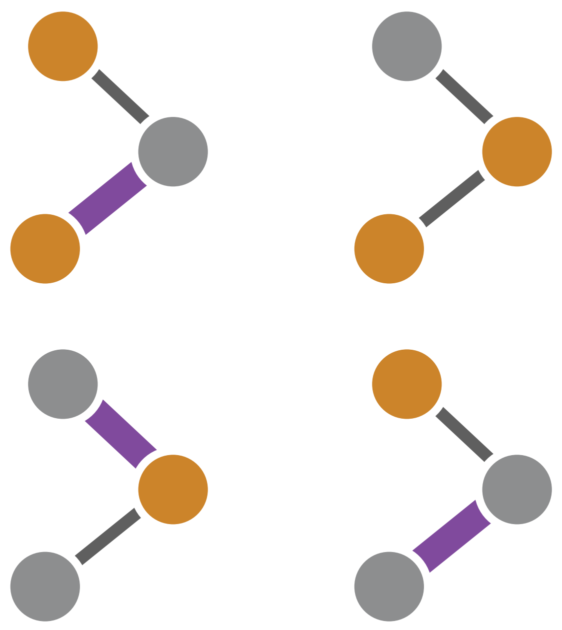
Integrated

good at displaying sets and clusters

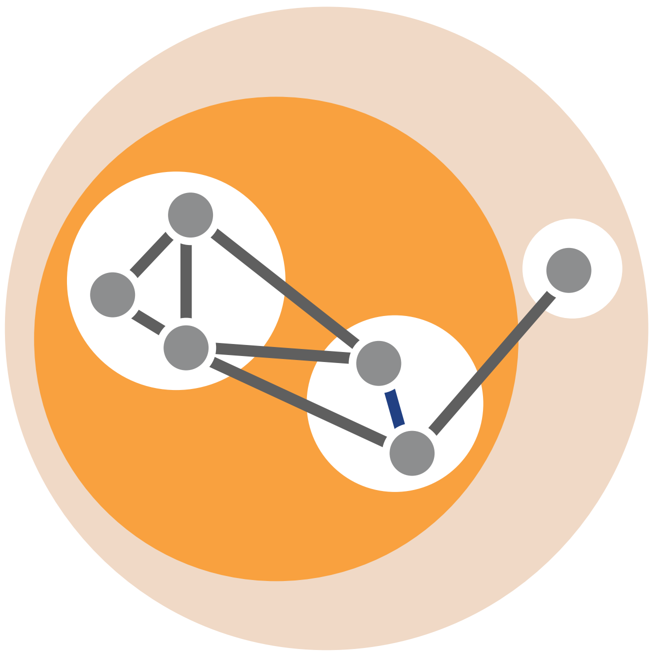
Not suitable for displaying more than one or two attributes at a time.

Recommended for recommend overloading for the particular use case of visualizing set-memberships or clusters on top of node-link diagrams

Layout Operations

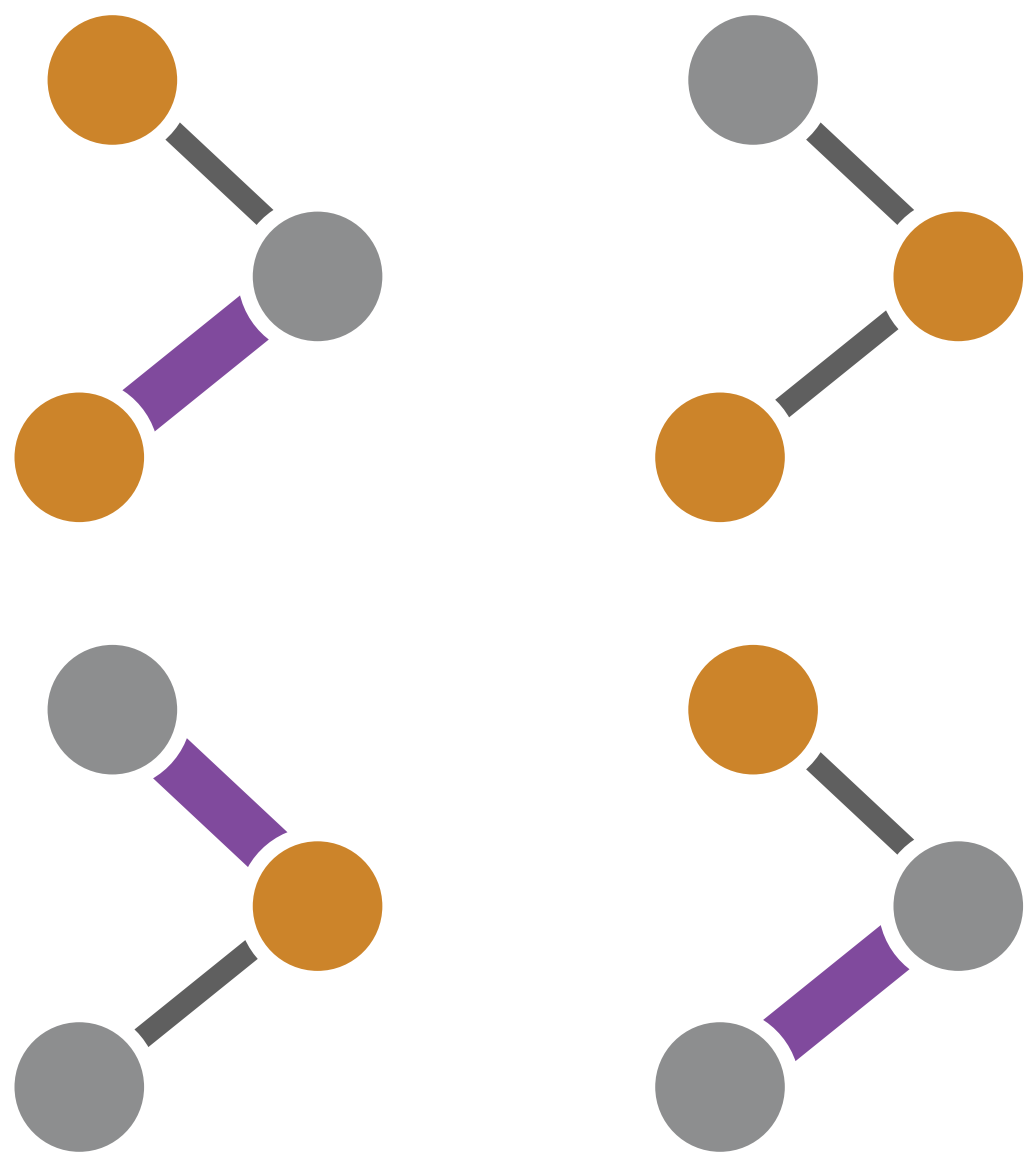


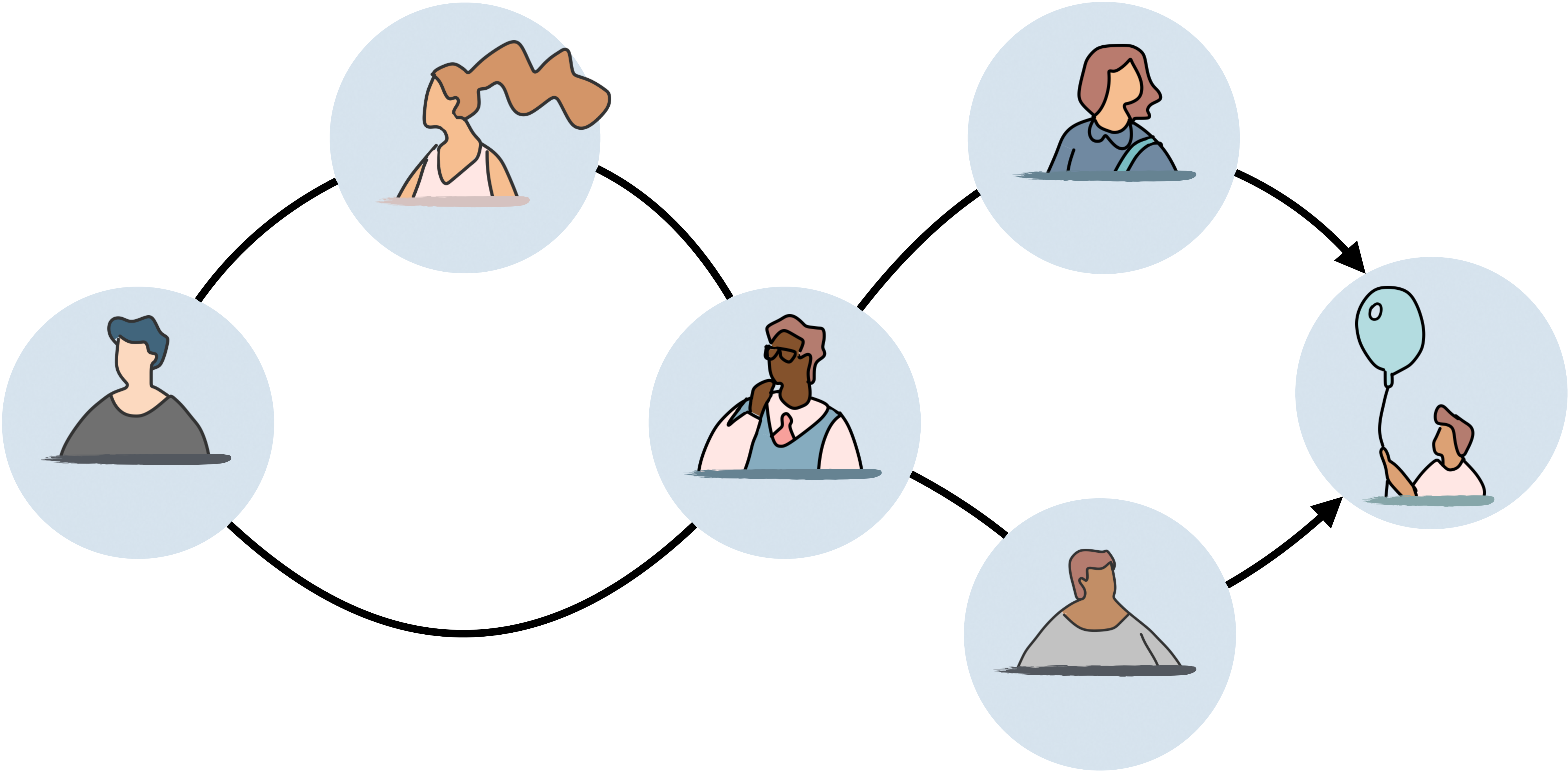
Small Multiples



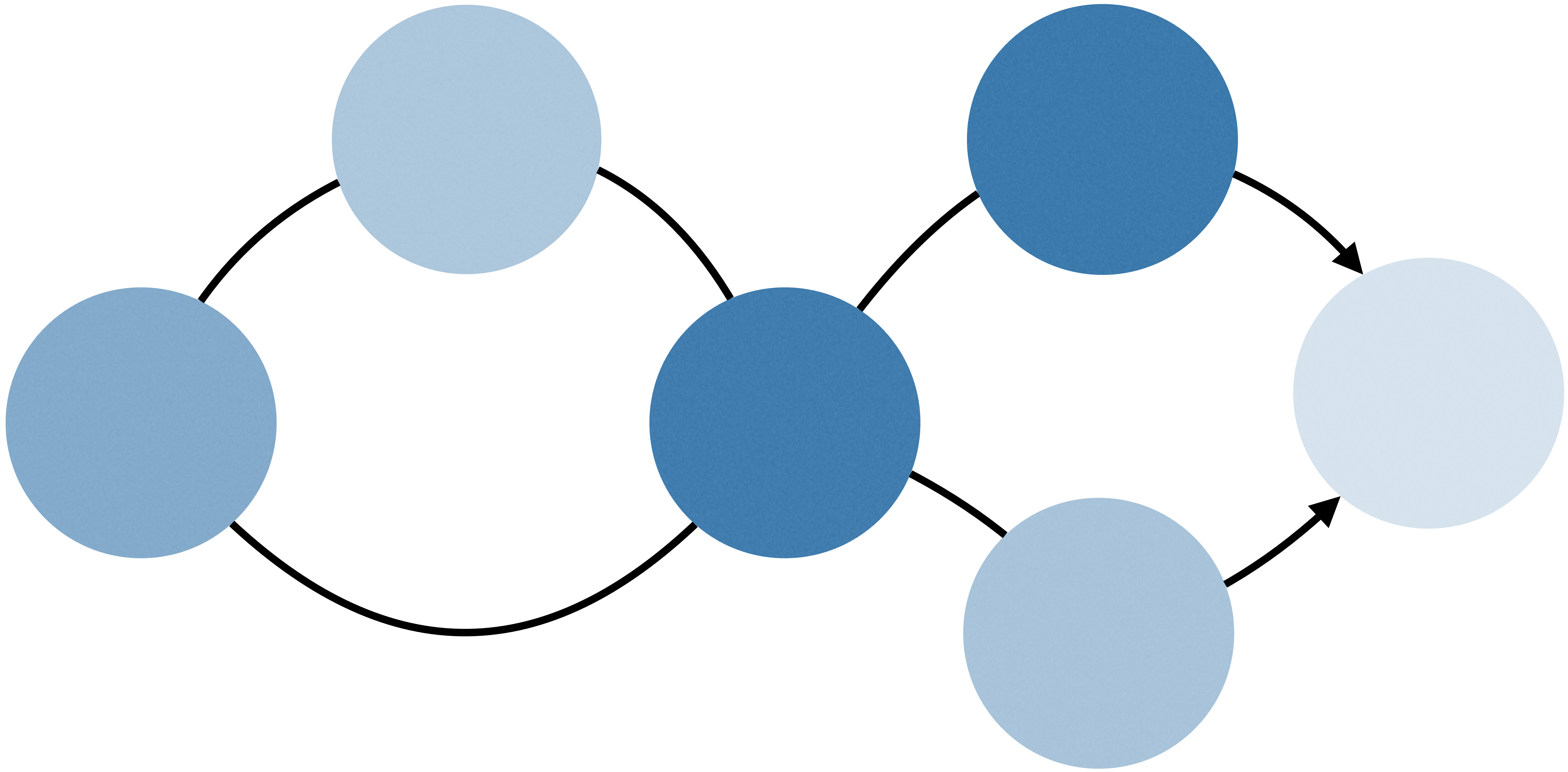
Hybrids

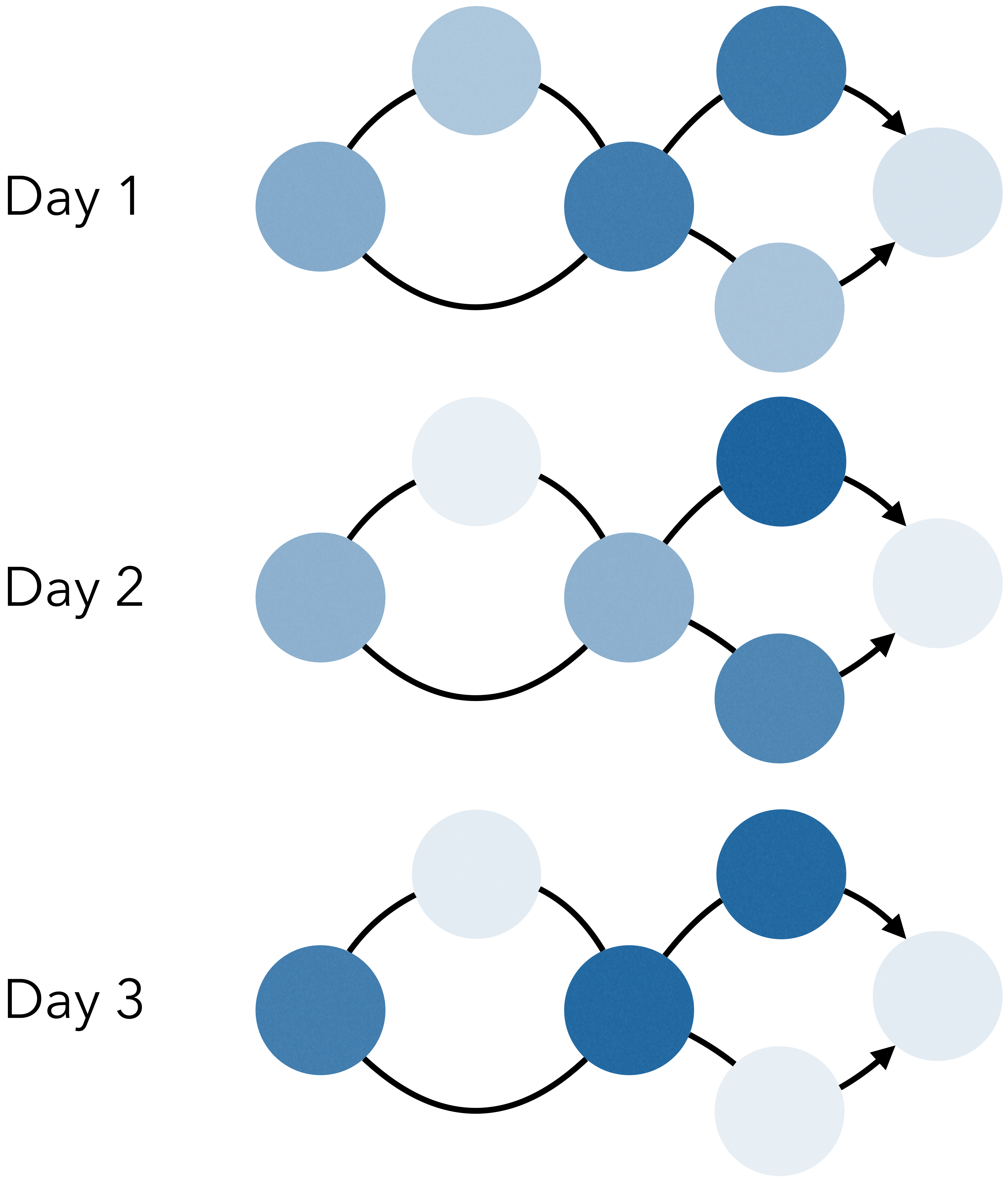
Small Multiples

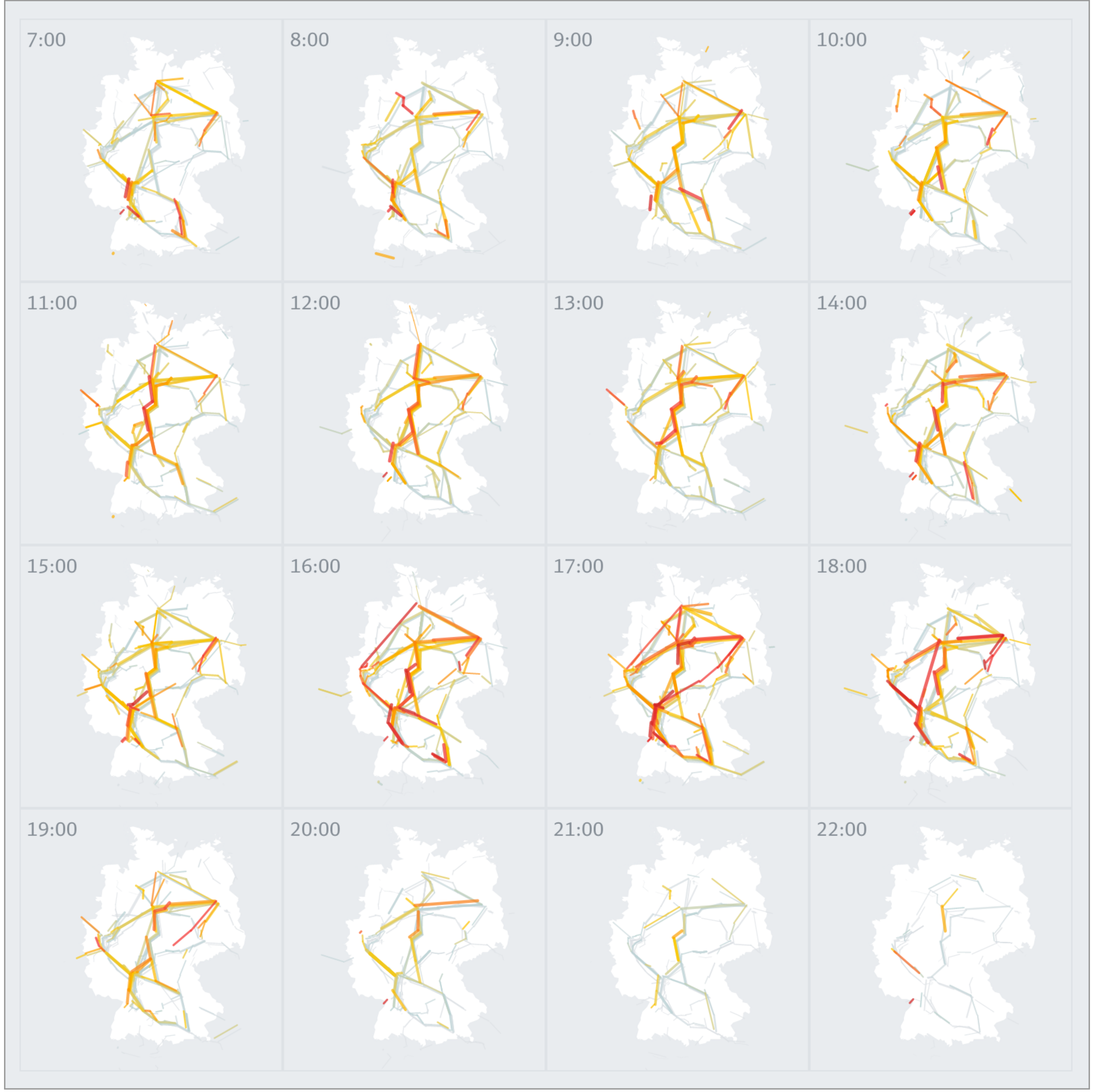




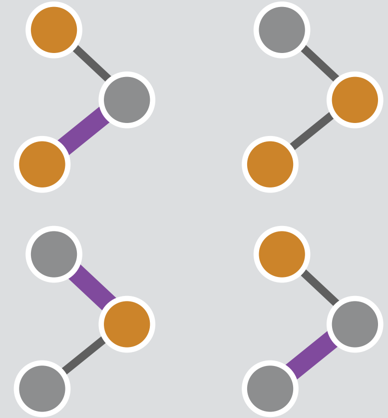
Day 1



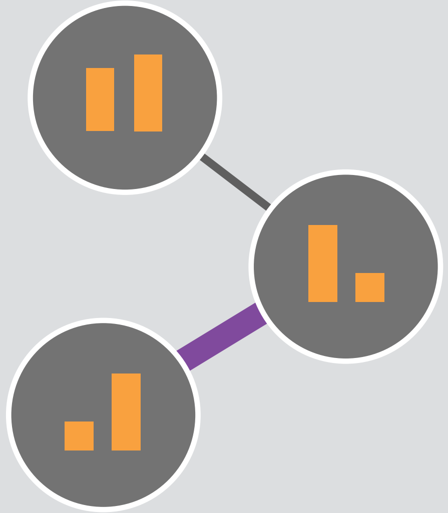

Day 1
Day 2
Day 3



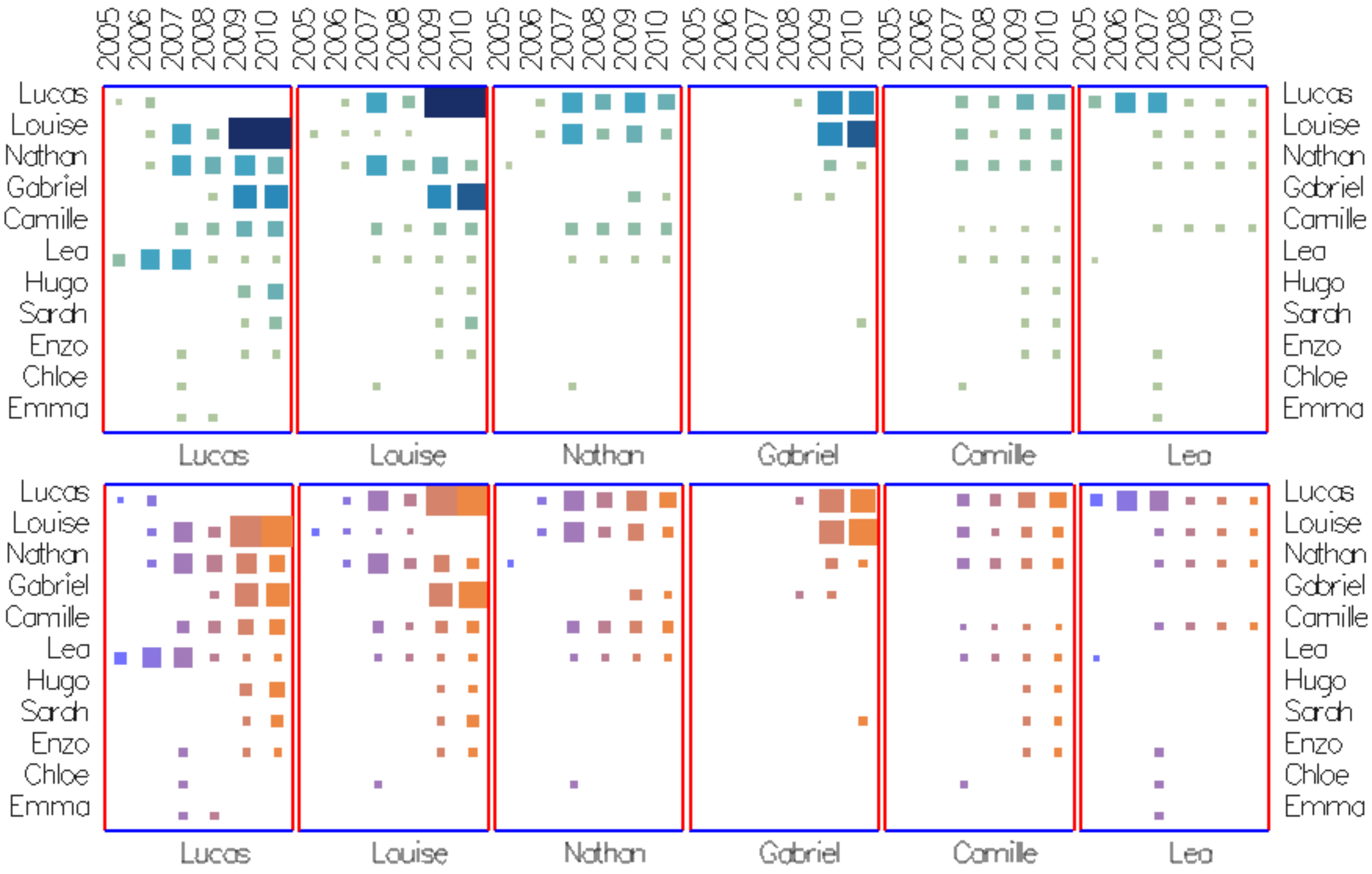
Peakspotting - https://truth-and-beauty.net/projects/peakspotting



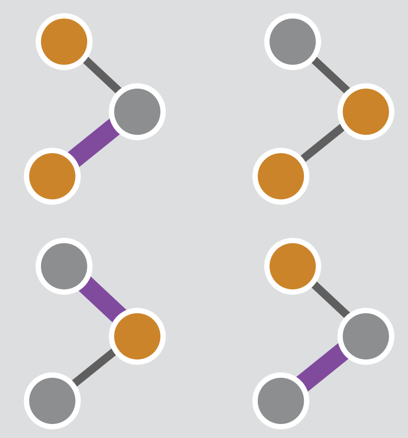
Small Multiples



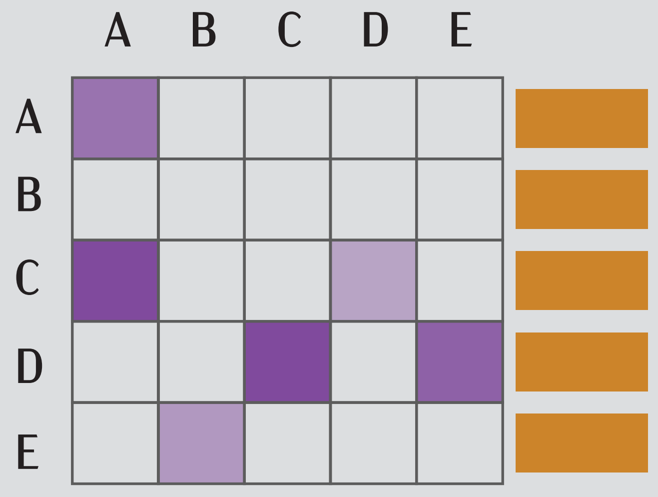
On-Node / On-Edge Encoding



Bach et al. 2014

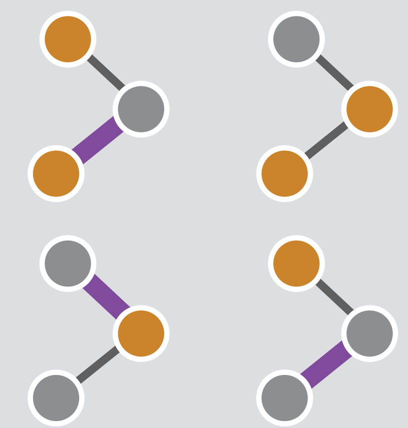


Small Multiples



Adjacency Matrix

Small Multiples



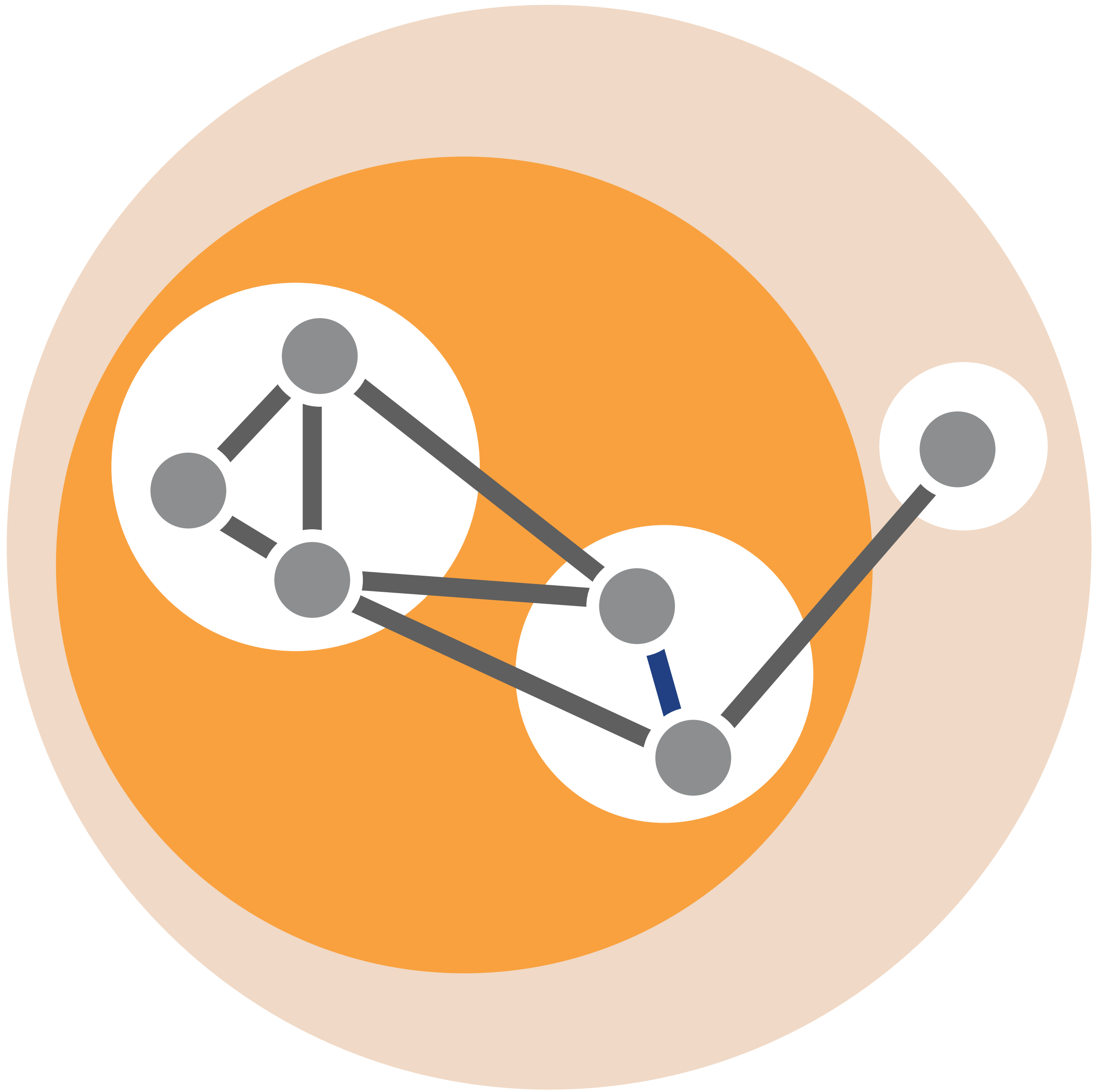
Small Multiples

Common layout facilitates attribute comparisons in specific topological features

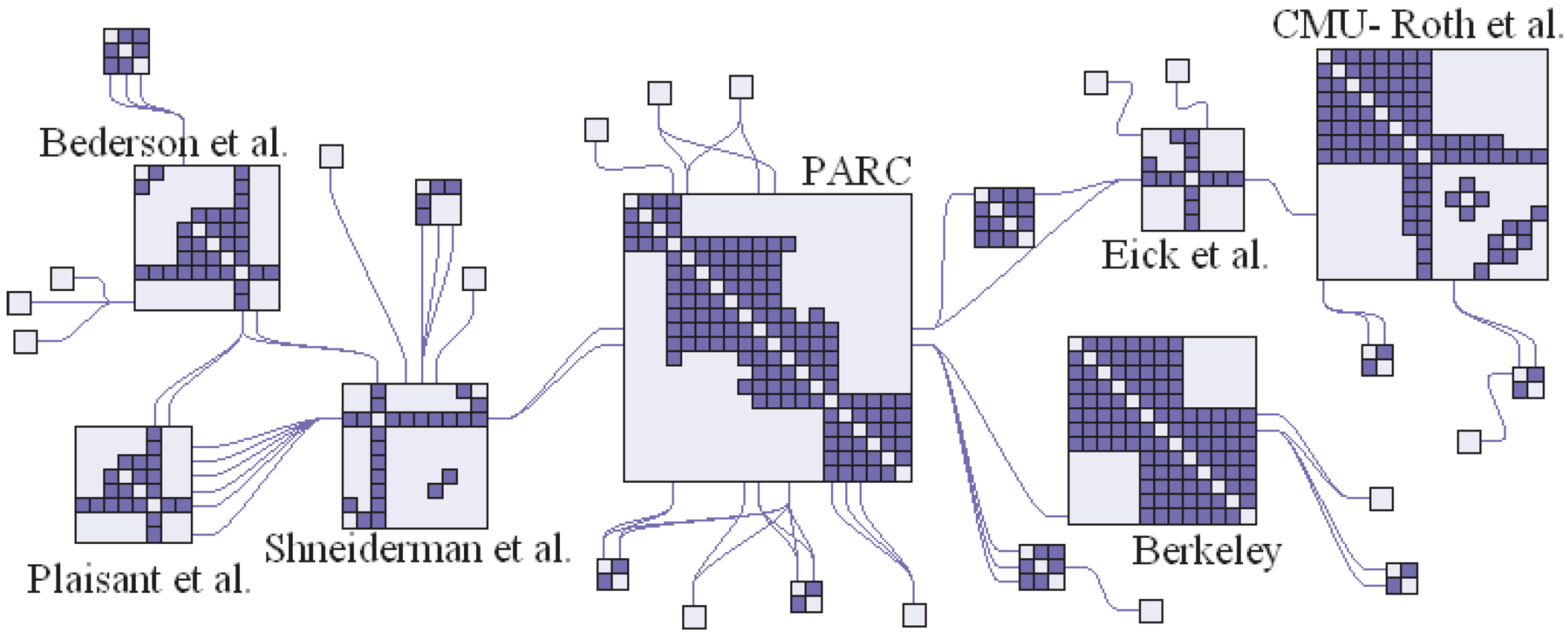
Not ideal for large networks, or tasks on clusters

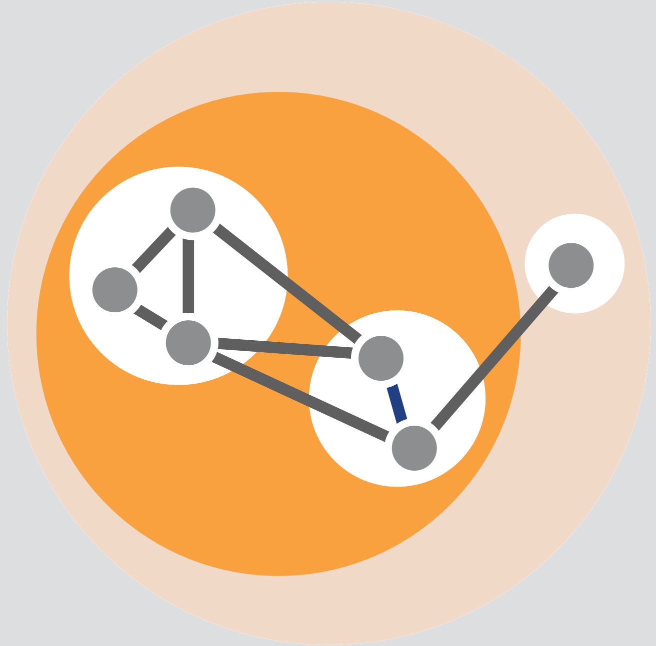
Recommended for small networks where the tasks are focused on attribute comparison

Hybrids



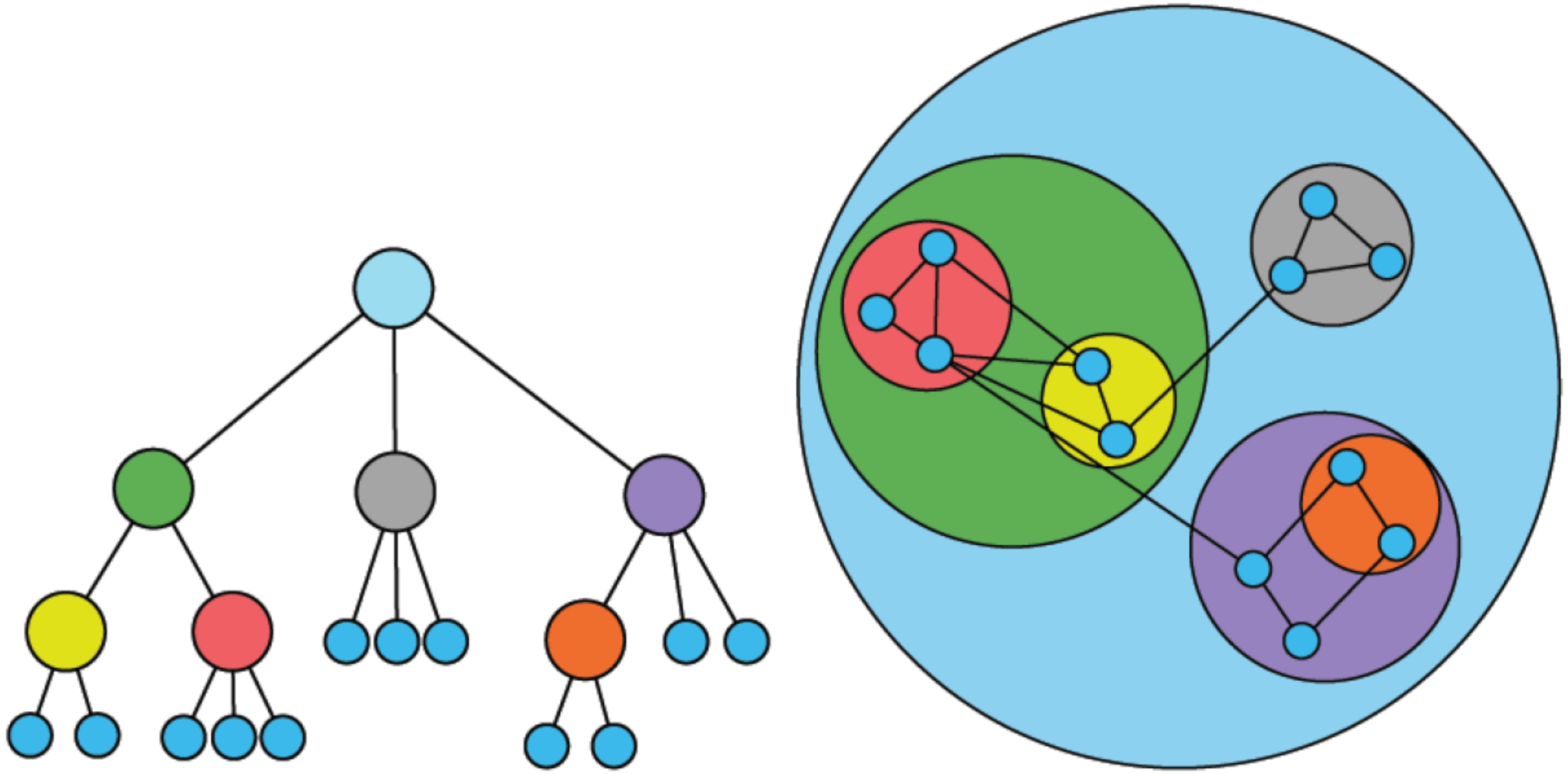
NodeTrix *Henry et al. 2007*

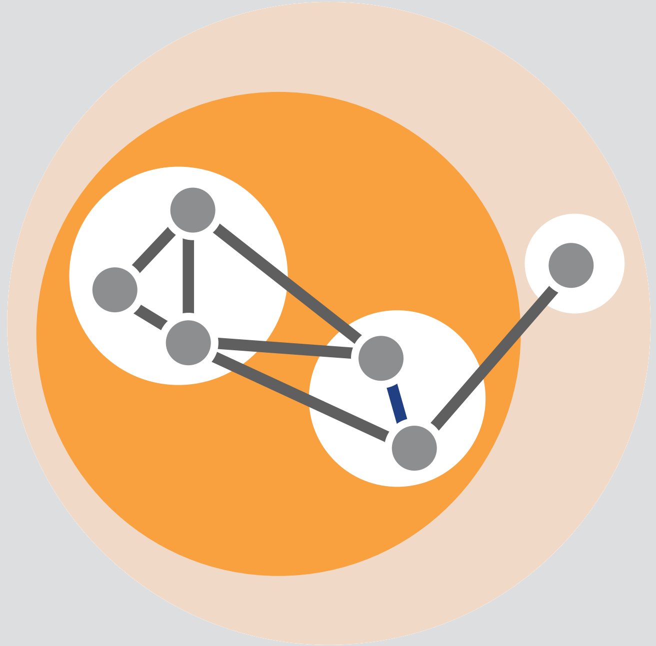




Hybrids

GrouseFlocks *Archambault et al. 2008*





Hybrids

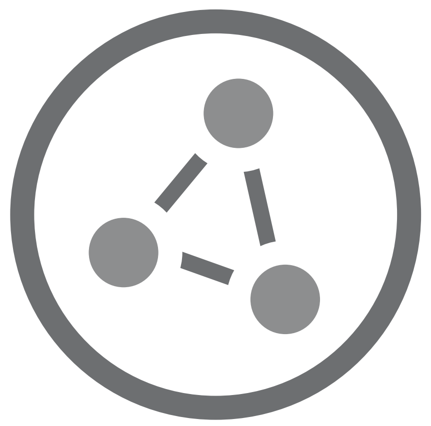
Hybrids

Can be useful for networks with irregular degree distribution

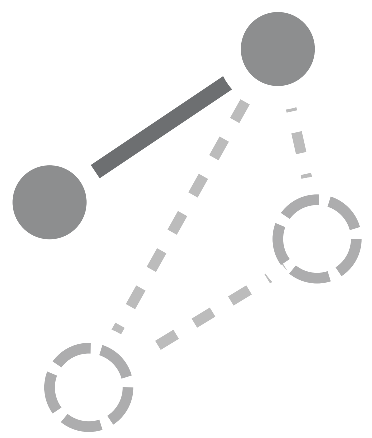
Adds complexity since users must parse different techniques simultaneously.

Recommended for networks with irregular degree distribution and few attributes

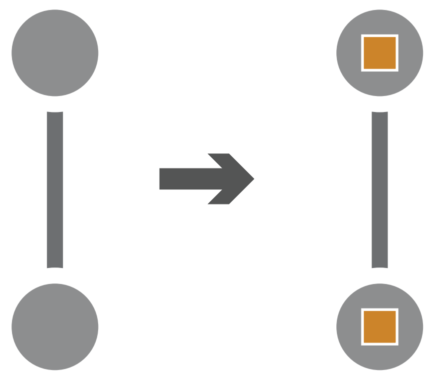
Data Operations



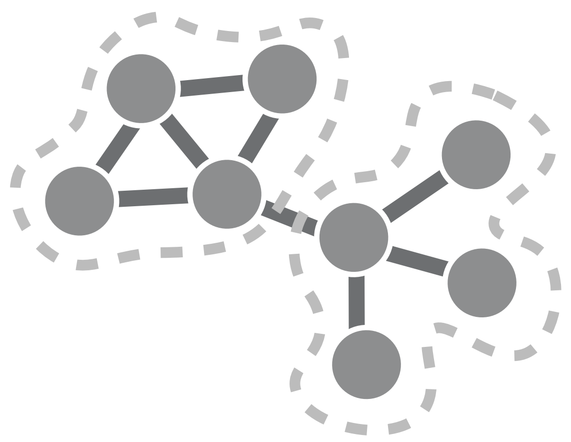
Aggregating Nodes/Edges



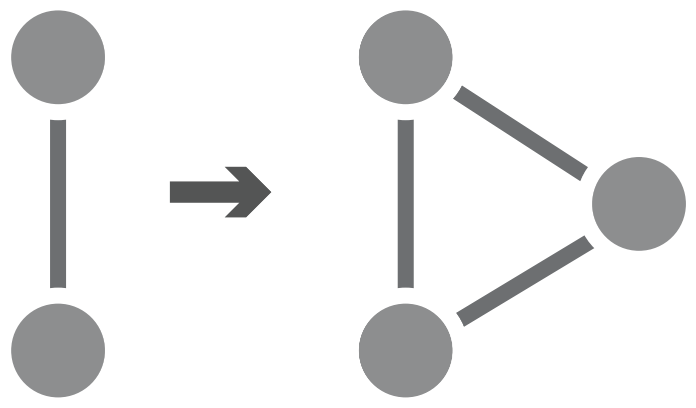
Querying and Filtering



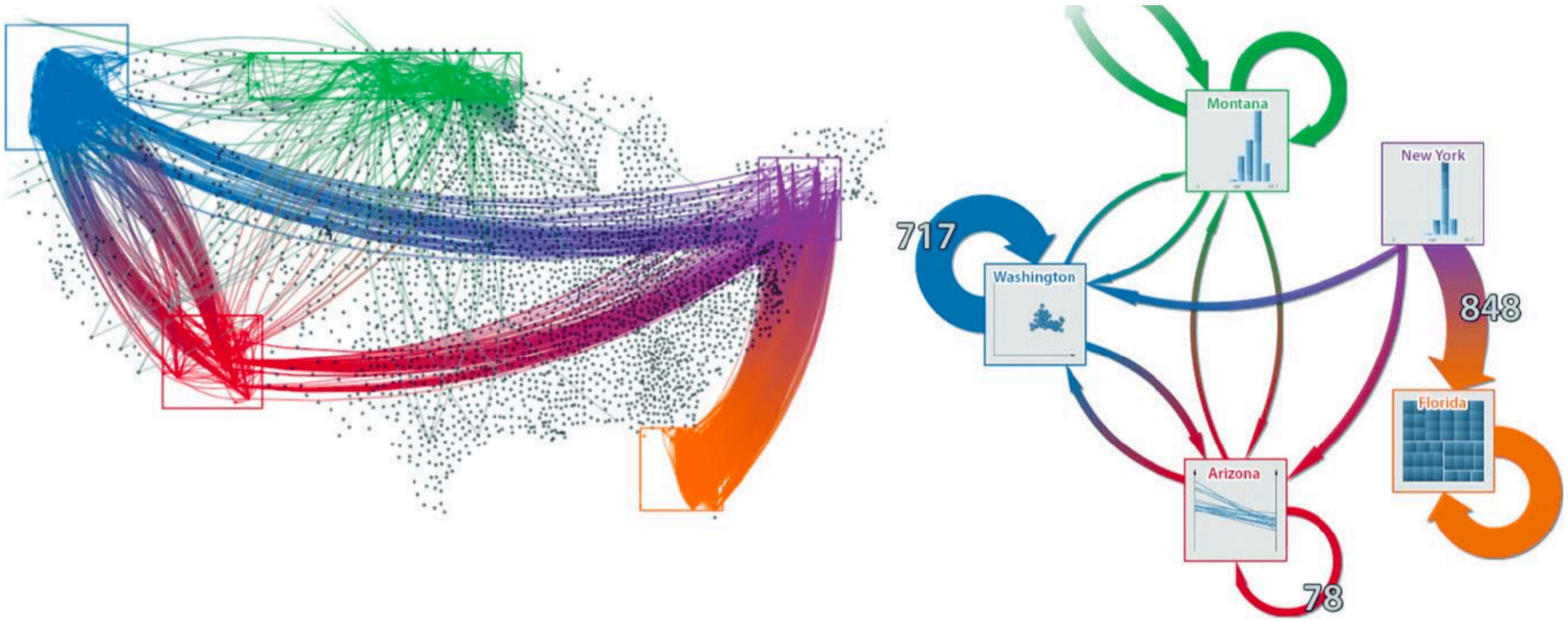
Deriving New Attributes



Clustering

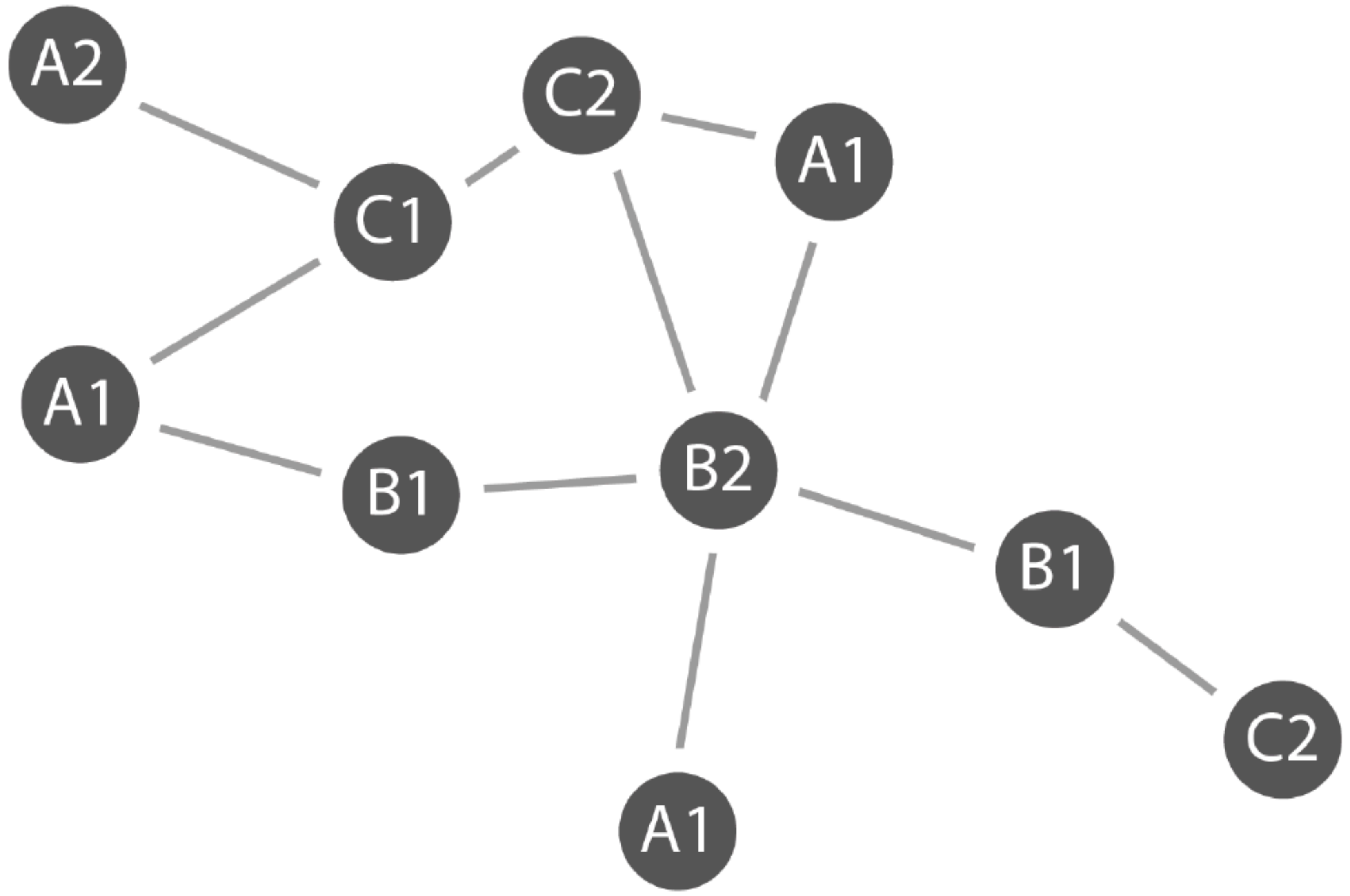


Converting Attributes/Edge to Nodes

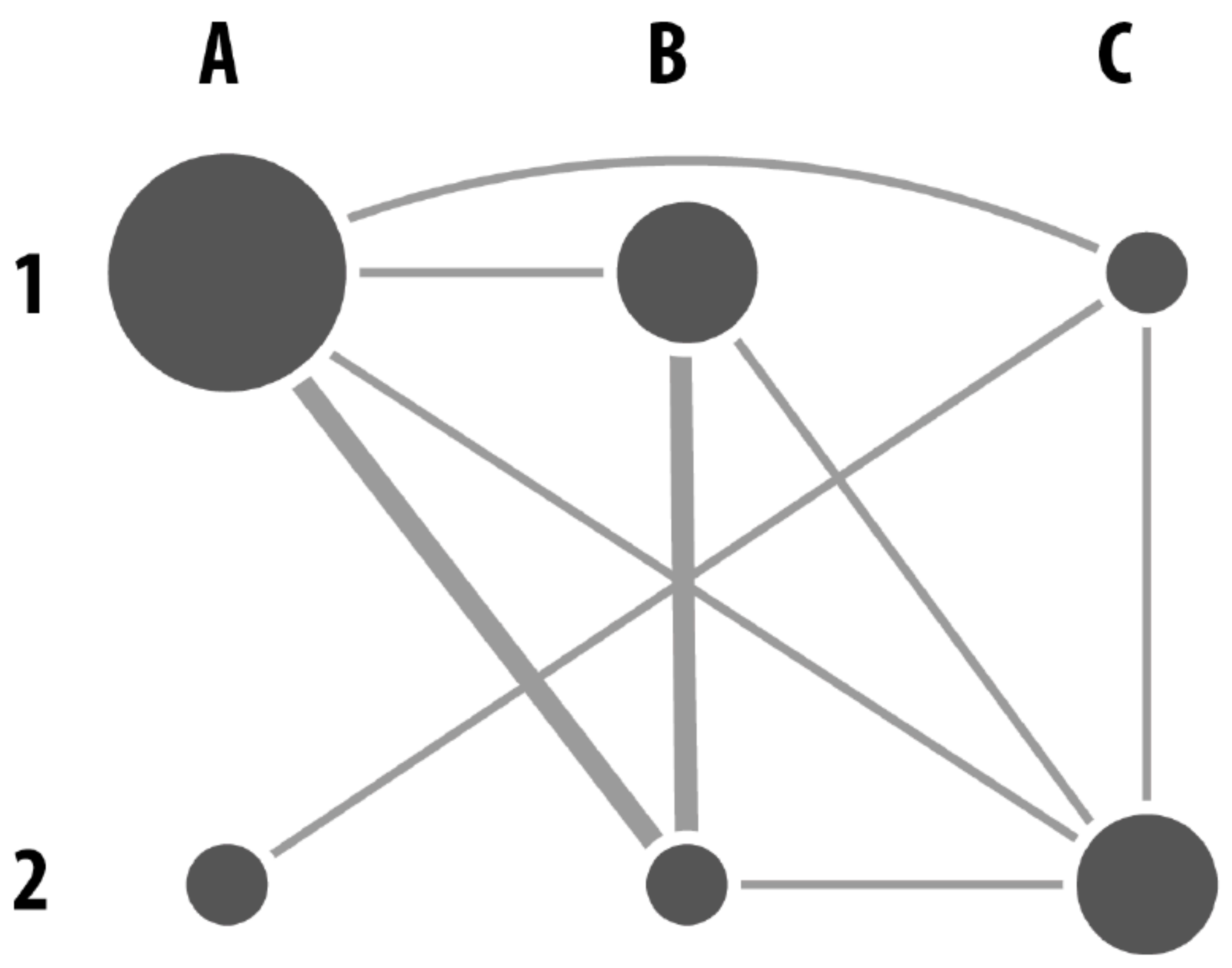


Elzen and Wijk, 2014

Aggregating Nodes/Edges



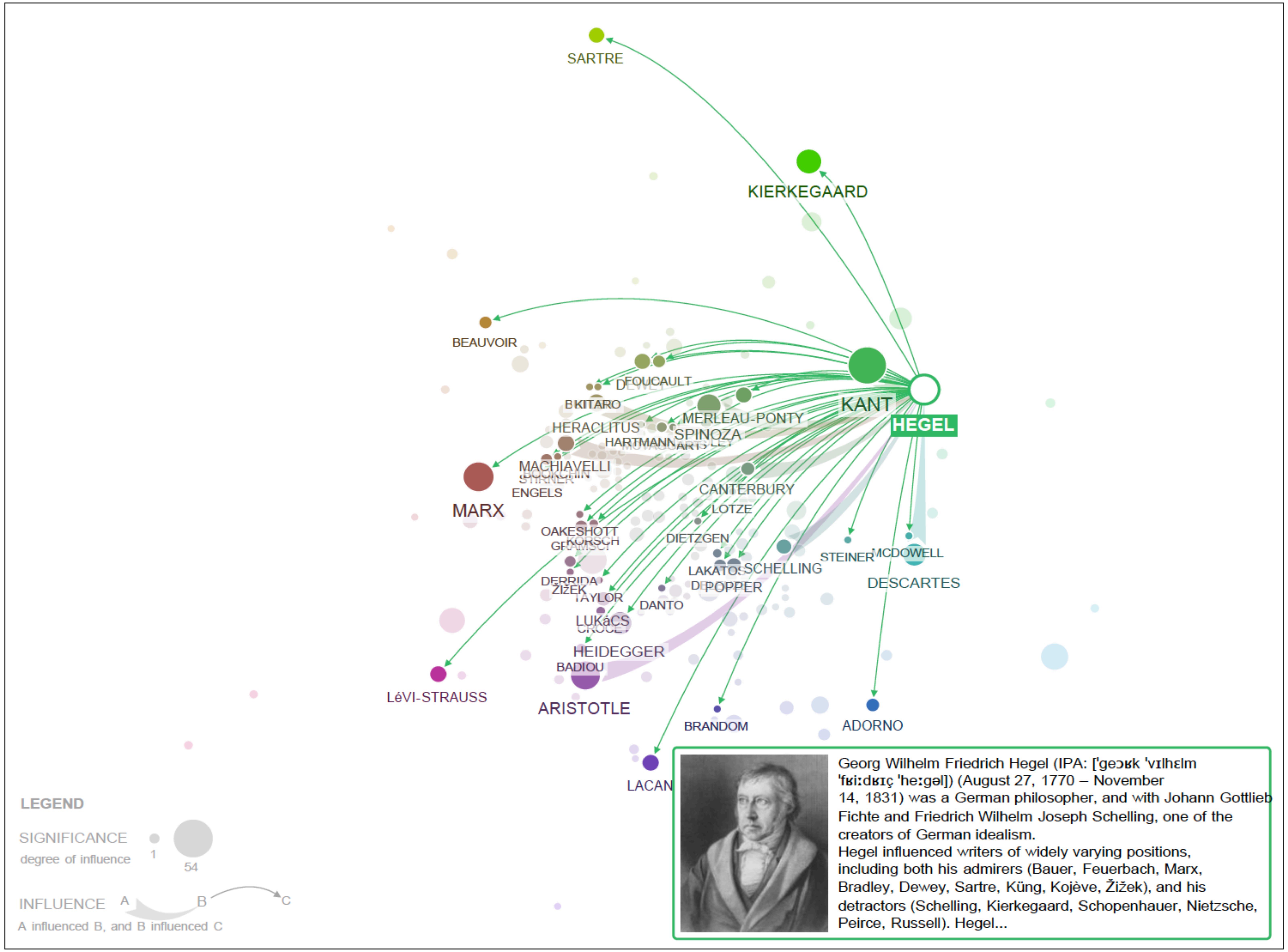
Node-Link Diagram



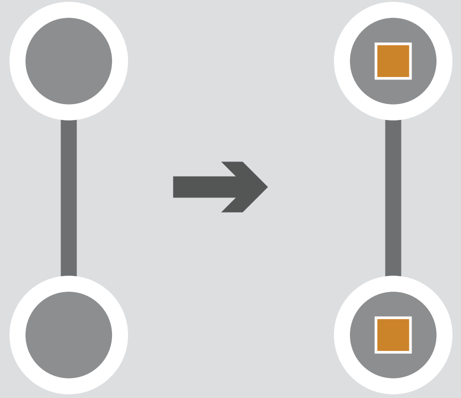
PivotGraph Roll-up

Wattenberg, 2006

Aggregating Nodes/Edges



Edge Map *Dork et al. 2011*



Deriving New Attributes

Convert

Connect

Edge projection

Toggle direction

Filter

Connective filter

Roll up edges

Create supernodes

Promote

Facet

Derive attribute

Derive connected attribute

Origraph

Interactive Network Wrangling

Alex Bigelow, Carolina Nobre, Miriah Meyer, Alexander Lex

WEDNESDAY, OCTOBER 23
2:20–3:50PM
Room: Ballroom A

Scoring Activity

		Size			Type				Node Attributes				Edge Attributes				Topolog. Structures				
		Small <100 nodes)	Medium (<1,000)	Large (>1,000 nodes)	Complex (sparse)	Complex (dense)	Layered/K-Partite	Trees	Few (<5)	Several (≥ 5)	Homog. (1 type)	Hetero. (>1 type)	Few (<3)	Several (≥ 3)	Homog. (1 type)	Hetero. (>1 type)	Single node/edge	Neighbors	Paths	Clusters	Entire/sub network
Node-Link Layouts	On-node/edge encoding																				
	Attr.-driven faceting																				
	Attr.-driven positioning																				
Tabular Layouts	Adjacency matrix																				
	Quilts																				
	BioFabric																				
Implicit	Inner nodes & leaves																				
	Leaves																				
View Operations	Juxtaposed																				
	Integrated																				
	Overloaded																				

0 This technique cannot support this data type or task.

1 This technique supports this data type or task very poorly.

2 This technique can support this data type or task, but is not ideal and may require interaction to achieve it.

3 This technique supports this data type or task very well.

Multivariate Network Visualization Techniques

A companion website for the STAR Report on Multivariate Network Visualization Techniques.

HOME   TECHNIQUES   WIZARD

About

This is a companion website for a review article on multivariate network visualization techniques.

Multivariate networks are networks where both the structure of the network and the attributes of the nodes and edges matter. It turns out, these are very common. Every person in a social network, for example, has both, relationships and lots of other characteristics, such as their age, the school they went to, or the city they live in. Multivariate network visualization techniques are designed to be able to show both, these attributes and the structure. Using these visualization techniques, we can analyze, for example, if a network of friends predominantly went to the same high school.

The visualization research community has developed many techniques to visualize these kinds of networks, and our review article – and this website – are designed to help you sort through these options.

Browse through the techniques illustrated below, or use our wizard to find the right multivariate network visualization technique for your datasets and tasks!

Get in touch if you have questions or comments.

Use the Wizard

Technique recommendations to fit your needs!

Navigate to the wizard tab and select your specific network characteristics, such as the size of the network and its type, and what tasks are relevant for your analysis and receive technique recommendations that are best suited to your selection.

Read the Review Article

The State of the Art in Visualizing Multivariate Networks
Carolina Nobre, Miriah Meyer, Marc Streit, and Alexander Lex
To appear in Computer Graphics Forum (EuroVis 2019)

vdl.sci.utah.edu/mvnv/